UNIVERSITY OF CALIFORNIA

Santa Barbara

Community College Transfer to Four-Year Institutions: A Latent Class Structural Equation Model

A Dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Education

by

Ryan Bradley Cartnal

Committee in charge:

Professor Russell W. Rumberger, Co-Chair

Professor Karen Nylund-Gibson, Co-Chair

Professor Michael Gottfried

September 2015

The dissertation of Ryan Bradley Cartnal is approved.

Michael Gottfried

Karen Nylund-Gibson, Co-Chair

Russell Rumberger, Co-Chair

June, 2015

Community College Transfer to Four-Year Institutions: A Latent Class Structural Equation Model

by

Ryan Bradley Cartnal

VITA OF RYAN CARTNAL

September 2015

Education

University of California, Santa Barbara
Ph.D. Educational Statistics and Measurement, September 2015
Dissertation: "Community College Transfer to Four-Year Institutions: A Latent Class Structural Equation Model"

University of California Extension, Santa Barbara
T.E.S.L Certificate, 1997

California State University, Bakersfield
M.A. Education, Cross Cultural Education, 1995

Occidental College, Los Angeles
A.B. Philosophy, 1991

American University, Washington, D.C.
The Washington Semester, 1989

Teaching Experience

Teaching Assistant:
University of California, Santa Barbara
Psychometrics: Classical Test Theory, Fall 2008

Associate Faculty, English as a Second Language (ESL):
Allan Hancock College, Santa Maria, 1995-1997
Cuesta College, San Luis Obispo, 1996-1997
Santa Barbara City College, 1996-1997

Professional Experience

Director of Institutional Research and Assessment
Cuesta College, CA, 2007 – Present

Supervisor of Institutional Research
Cuesta College, CA, 2005 – 2007

Institutional Research Analyst
Cuesta College, CA, 1997 – 2005

Student Advisor
Cuesta College, CA, 1994 – 1997

Assistant to the President for Enrollment and Retention
Taft College, CA, 1992 – 1994

Professional Basketball Player/English Language Instructor
Basket Club De Vallespir, Amelie Les Baines, France, 1991 – 1992

Awards and Fellowships

Community College Research Assistantship 2008/09

Publications

Diaz, D. P., & Cartnal, R. B. (1999). Students' learning styles in two classes: Online distance learning and equivalent on-campus. College teaching, 47(4), 130-135.

Diaz, D., & Cartnal, R. (2006). Term length as an indicator of attrition in online learning. Innovate: Journal of Online Education, 2(5), 7.

Professional Affiliations

Accrediting Commission for Community and Junior Colleges (ACCJC)
American Educational Research Association (AERA)
Association for Institutional Research (AIR)
National Council on Measurement in Education (NCME)
The Research and Planning Group for California Community Colleges (The RP GROUP)

Graduate Coursework

Quantitative
Introductory Statistics, Inferential Statistics, Linear Models for Data Analysis, Advanced Multivariate Statistics, Non-Parametric Statistics, Survey Research Design, Survival Analysis, Hierarchical Linear Models, Structural Equation Modeling, Classical Test Theory, Advanced Psychometrics, Item Response Theory, Single Case Experimental Design

Qualitative
Introduction to Qualitative Research, Ethnography, Narrative Analysis, Discourse Analysis

ABSTRACT

Community College Transfer to Four-Year Institutions: A Latent Class Structural Equation Model

by

Ryan Bradley Cartnal

Drawing on data from the nationally representative 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS 04/09), this study proposed and tested a latent class measurement model of public two-year community college student transfer subtypes, and examined the latent class conditional structural relationships among student background characteristics, Remediation, First-year college GPA, Student Engagement and transfer to four-year institutions. Perhaps, most importantly, this study examined whether latent class membership moderated the relationships between malleable factors and four-year transfer likelihood. This study employed latent class analysis (LCA) to identify potential latent transfer subtypes, confirmatory factor analysis (CFA) to account for the unreliability in the indicators of the hypothesized latent student Engagement factor, and structural equation modeling (SEM), using an unbiased 3-step approach to the analysis of both predictors of latent class and latent class prediction of distal outcomes (Asparouhov & Muthén, 2014a; Vermunt, 2010), to examine the associations among the above mentioned variables and four-year transfer likelihood. Based on a comprehensive review of information criteria and fit indices, a four class solution fit the data best and provided four substantively relevant transfer classes which I labeled as follows: *Class 1:High Transfer Intentions, Few Barriers, Class 2: Low Transfer Intentions, Some Barriers, Class 3: Moderate Transfer Intentions, Low Academic Resources, Class 4: Moderate Transfer Intentions, Low Academic*

Momentum. Controlling for latent class membership, first generation college status and exposure to remediation were negatively associated with four-year transfer likelihood, while increases in both first-year GPA and student Engagement were positively associated with transfer outcomes. However, when latent class specific slopes were estimated, exposure to Remediation and first-year GPA were statistically significantly ($p<.05$) related to transfer only in *Class 1:High Transfer Intentions, Few Barriers*, while only First Generation Status was statistically significantly related to transfer in *Class 3; Moderate Transfer Intentions, Low Academic Resources* and *Class 4: Moderate Transfer Intentions, Low Academic Momentum*; student Engagement, at an inflated alpha of .10, was statistically significantly (p=.07) related to transfer in *Class 4: Moderate Transfer Intentions, Low Academic Momentum*.

That latent class membership moderated the relationships between malleable factors and transfer likelihood provides underfunded community colleges with a more nuanced answer as to which variables are related to transfer. Using such information, community colleges could provide class-specific advice and interventions, rather than a one size fits all approach, which may or may not be right for each transfer subtype. In this way, community colleges may increase transfer rates in an efficient and strategic manner that meets the needs of its diverse student population.

TABLE OF CONTENTS

TABLE OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

The number of public two-year community college students who eventually transfer to four-year institutions is low by any definition. According to the most recent nationally representative survey of first-time postsecondary students (BPS:04/09), nearly 82% of 2003/04 first-time community college students intended to transfer and only roughly 27% did so within six years (Skomsvold, Radford, & Berkner, 2011). The gravity of this intent/transfer gap is weighted further by the fact that approximately 43% of all beginning postsecondary students in 2003/04 attended a public two-year community college (Berkner & Choy, 2008).

Compared to four-year entrants, community college students are more likely to be members of historically underrepresented racial/ethnic groups as well as first-generation college students. Given that baccalaureate degree attainment is strongly associated with increased economic, health, and social benefits, particularly for historically underrepresented students (Belfield & Bailey, 2011; Black & Smith, 2006; Brand, 2010; Brand & Xie, 2010; Herd, Goesling, & House, 2007; Hout, 2012; Lange & Topel, 2006; Yang, 2008), such low transfer rates translate into decreased opportunities for the very students who stand to gain the most from transfer and eventual bachelorette degree attainment (Brand, Pfeffer, & Goldrick-Rab, 2012; Brand & Xie, 2010).

However, unlike four-year beginners, who are assumed to have degree expectations of at least a baccalaureate degree, determining the actual degree expectations of community college beginners—because community colleges provide opportunities to pursue more than one educational goal (e.g., transfer preparation, vocational training, remediation, etc.)—is a non-trivial endeavor (Bradburn, Hurst, & Peng, 2001; Spicer & Armstrong, 1996). In addition, because community colleges are open access institutions, community college students' incoming skill levels vary widely compared to four-year beginners who all must meet specific minimum admission requirements (Cohen, Brawer, & Kisker, 2013). Finally, unlike most four-year institutions, community colleges do not require students to enroll full-time, thus creating wide variation in students' enrollment intensities and thus their potential for engagement with both college and external demands (Adelman, 2005b, 2006; Goldrick-Rab, 2007).

Because of this heterogeneity among community college students' degree expectations, incoming academic skill levels, enrollment intensity and engagement with both college and external demands, it is unclear whether potentially malleable factors associated with transfer will have the same relationships across this diverse population of postsecondary beginners.

Therefore, based on a nationally representative sample of community college beginners, this study examined community college transfer from the perspective that relationships between malleable student experiences, academic performance, and eventual transfer may not be the same for students classified into different hypothesized latent transfer subtypes. First, using a latent class analysis approach, students were classified into transfer subtypes, which consisted of students who began college with similar item response patterns across several indicators known to correlate with transfer. Second, latent class conditional relationships between student background characteristics, remediation, first-year community college grade point average (GPA), student engagement and transfer likelihood were estimated. The final model tested whether latent transfer subtype moderated these relationships.

In this introduction I provide a brief overview of the community college transfer function, noting differences between community college and four-year student profiles, as well as highlighting differential probabilities of transfer for different groups of community college students.

1.1: Community College Transfer Background

Public community colleges serve multiple, evolving, and in some ways paradoxical functions within the United States postsecondary educational landscape. True to their original purpose, preparing students to transfer to four-year institutions remains not only a primary mission, but also a core indicator by which legislators and the public assess the continued viability of community colleges (Adelman, 2005a, 2006; Cohen et al., 2013; Desai, 2011; Dougherty & Townsend, 2006; Schmidtke, 2012; Witt, Wattenbarger, Gollattscheck, & Suppiger, 1997).

Without diminishing the clear economic and social benefits associated with completing an academic or vocational associate degree or certificate (cf. Belfield & Bailey, 2011), or gaining important basic skills (e.g., learning English, Adult Basic skills, etc.), baccalaureate degree attainment is more strongly associated with increased economic, health, and social benefits, particularly for historically underrepresented students (Belfield & Bailey, 2011; Black & Smith, 2006; Brand, 2010; Brand & Xie, 2010; Herd et al., 2007; Hout, 2012; Lange & Topel, 2006; Yang, 2008). However, for many students, direct entry into four-year institutions is limited by substandard prior academic achievement, lack of financial resources, family obligations, and/or four-year institution impaction, etc. (Cohen & Brawer, 2008). For these students, community colleges provide access to an alternate postsecondary route toward a baccalaureate degree. Indeed, several studies suggest that the likelihood of baccalaureate degree attainment for community college students who *do* transfer to four-year institutions is roughly equivalent to that of similar students who began at four-year institutions (Lee, Mackie-Lewis, & Marks, 1993; Melguizo, Kienzl, & Alfonso, 2011; Monaghan & Attewell, 2014). Nevertheless, in order to have a shot at completing a baccalaureate degree, community college students must first successfully transfer to a four-year institution.

Although open access community colleges have succeeded to a large extent in the *democratization* of postsecondary educational access, most studies find a vestigial *caste like* distribution of postsecondary outcomes. (Dougherty & Kienzl, 2006; Leigh & Gill, 2003; Ogbu, 1978; Rouse, 1995, 1998). Reflective of community colleges' relative success in the *democratization* of postsecondary access, compared to students beginning at four-year institutions in 2003/04, community college beginners were more likely to come from families with lower educational attainment and income levels, to be female, older, non-white, and to have both lower high school academic achievement and entering college admission test scores (Berkner & Choy, 2008).

Notwithstanding the difficulty in identifying community college students' actual degree plans, nearly 82% of first-time community college students in 2003/04 (compared to 97.9% among four-year beginners) indicated degree aspirations of at least baccalaureate degree attainment. Given that with few exceptions baccalaureate degrees must be completed at four-year institutions, it is clear that the number one *stated* goal for community college students involves transfer to a four-year institution.

Unfortunately, whereas public two-year community colleges have extended postsecondary access to students who were traditionally underrepresented at four-year institutions, the overall percentage of students who eventually transfer to four-year institutions is low. For example, among all community college beginners in 2003/04, only 26.6% transferred to a four-year institution within six years. Furthermore, transfer rates for Black (24.6%) and Hispanic (21.9%) students were lower than for White (28.9%) and Asian/Pacific Islander (46.3%). Similarly, transfer rates for students whose parents had completed only a high school degree (13.7%) were significantly lower than for students whose parents had completed a baccalaureate degree (26.6%) (Horn & Skomsvold, 2011).

Given the clear benefits associated with baccalaureate degree completion, and that nearly half of all beginning postsecondary students begin their educational journey at community colleges—82% of whom *aspire* eventually to complete a baccalaureate degree or higher—it is important to better understand the associations among malleable student experiences, academic performance and students' likelihood of transfer to a four-year institution. This issue is particularly meaningful for historically underrepresented students who are both overrepresented in community colleges and significantly underrepresented with respect to four-year transfer success.

1.2: Student Level Variables Associated with Transfer

Generally, the more closely a community college student resembles a typical four-year college student, the greater the probability of transfer (Deil-Amen, 2012). While this is an oversimplification, the transfer research literature, by and large, supports this conclusion.

Beginning with student background characteristics, White and Asian community college students have greater odds of transferring to a four-year institution than Black, Hispanic, or students from other racial/ethnic backgrounds (Grubb, 1991; Wang, 2012). Additionally, students from lower socioeconomic (SES) backgrounds are significantly less likely to transfer than students who come from moderate or high SES backgrounds (Bradburn et al., 2001; K. J. Dougherty & G. S. Kienzl, 2006; A. C. Dowd, Cheslock, &

Melguizo, 2008). Finally, female students, who, historically, were less likely to transfer, recently have outpaced their male counterparts with respect to transfer likelihood (Dougherty & Kienzl, 2006; Horn, 2009; Roksa, 2006).

Similarly, community college students with strong academic resources from high school are significantly more likely to transfer than those with weaker academic resources. In other words, community college students who are academically prepared for college through completion of a rigorous high school curriculum, with solid academic achievement and higher standardized test scores are significantly more likely to transfer (Adelman, 2006; Bradburn et al., 2001; K. J. Dougherty & G. S. Kienzl, 2006; Kalogrides & University of California, 2008; V. E. Lee & Frank, 1990; Long & Kurlaender, 2009; Nora & Rendon, 1990; Porchea et al., 2010; Velez & Javalgi, 1987).

Because community colleges provide credentials other than the traditional transfer preparation function, students' degree expectations and transfer intentions signficantly affect the likelihood of transferring. In fact, many researchers limit their analyses to include only students with a stated goal of four-year transfer (Bradburn et al., 2001; Spicer & Armstrong, 1996). I do not limit my analysis in this way, however, because some students who do not intend to transfer actually do, while a large proportion of students who do intend to transfer do not. For example, among community college beginners in 2003/04, nearly 13% of students who did not indicate transfer as their educational goal eventually transferred to a four-year institution within five years, while roughly 62% of students who did indicate a goal of four-year transfer failed to transfer in five years (NCES Powerstats).

In addition to transfer intentions, external demands, such as working full time and/or raising children also affect transfer likelihood. Specifically, working full-time as well as being financially independent and/or having dependents both result in lower odds of transfer (Bradburn et al., 2001; K. J. Dougherty & G. S. Kienzl, 2006; Kalogrides & University of California, 2008; V. E. Lee & Frank, 1990).

Related in many cases to students' external demands, students' initial academic momentum is predictive of transfer outcomes. That is, students who delay postsecondary entry after high school and/or do not enroll full-time are significantly less likely to transfer than students who do not delay entry and enroll full-time. Similarly, students who enroll continually from term to term are more likely to transfer than are students who stop out between terms (Adelman, 2005a, 2006; Attewell, Heil, & Reisel, 2012; Doyle, 2011).

With respect to student experiences in college, students with higher levels of academic engagement generally have higher likelihoods of transfer, though the literature is somewhat mixed on this topic. Essentially, students who are engaged with faculty outside of class, participate in study groups, meet with advisors, etc. are, in general, more likely to transfer (Deil-Amen, 2011; LaSota, 2013; Lee & Frank, 1990; Quaye & Harper, 2014). Given the somewhat inconclusive role that student engagement plays in community college transfer likelihood, the results of this study may shed more light on this topic.

Perhaps one of the most contentious, contemporary issues in the study of transfer and other community college outcomes is whether remediation has deleterious or ameliorative effects on students' likelihood of transfer and other community college outcomes (Bahr, 2008b; Calcagno, Crosta, Bailey, & Jenkins, 2007; Calcagno & Long, 2008; Crisp & Delgado, 2014). Moreover, it is unclear whether the mostly negative effects of remediation on transfer likelihood are reflective of students' low academic resources or if it is the added time required to move through remedial sequences, or both, that reduces the odds of transfer (Jones, 2012).

Clearly, the bivariate correlation between remediation and transfer is negative. However, once conditioned on the aforementioned variables, there is some disagreement, depending on the research design, the particular subjects considered (e.g., Math, English, etc.), and when in a student's college career the remediation occurs, whether remediation affects different students in different ways (Crisp & Delgado, 2014; Crisp & Nuñez, 2014). This study may contribute significantly to the research literature by examining the differential relationships between remediation and transfer across different hypothesized transfer subtypes.

Finally, students' academic performance, especially in the first year of college, is statistically significantly associated with an increased likelihood of four-year transfer (Hagedorn, Cypers, & Lester, 2008; Wang, 2009, 2012). Specifically, students who achieve higher grade point averages in college level courses, especially in the first year of enrollment, are more likely to transfer than students with lower grade point averages. Although it may appear obvious that community college academic achievement would correlate with increased odds of transfer, the current study asks further whether this relationship is the same for different transfer subtypes.

1.3: Institutional and State Level Variables Associated with Transfer

While the research literature regarding the impact of institutional and state level variables on transfer likelihood is meager in comparison to what is known about student level factors, there are a handful of studies that have examined rigorously institutional and state level characteristics, processes, and policies and their association with transfer.

With respect to fixed structural characteristics, some studies indicate that college enrollment and/or the number of full-time equivalent students is related to transfer outcomes, though the direction of this relationship varies across studies (Calcagno, Bailey, Jenkins, Kienzl, & Leinbach, 2008; Chen, 2012; LaSota, 2013; Porchea, Allen, Robbins, & Phelps, 2010).

Similarly, the research literature is mixed when examining the association between student compositional characteristics and transfer. Some studies find that, after controlling for student level variables, community colleges with greater percentages of minority students (Calcagno et al., 2008; Wassmer, Moore, & Shulock, 2004), older students, or students with vocational majors/completions (LaSota, 2013) decrease the probability that students will transfer. Likewise, there is some evidence that greater overall college transfer rates may increase the probability of transfer at the student level (LaSota, 2013).

One institutional level variable that has received considerable attention in the literature is the proportion of part-time faculty at community colleges. With few exceptions (Porchea et al., 2010), most studies indicate that the proportion of part-time faculty in community colleges is negatively associated with degree and transfer outcomes (Calcagno et al., 2008; Jacoby, 2006; Kevin Eagan & Jaeger, 2009; Lynch, 2007).

At the state level, while a few studies have examined the impact of articulation or common course numbering on transfer outcomes, the findings are inconclusive at best (Anderson, Sun, & Alfonso, 2006). However, some studies indicate that higher levels of community college tuition, which are typically set at the state level, result in higher transfer probabilities (Porchea et al., 2010). Similarly, Yang (2005) found that larger gaps between two and four-year tuition costs were negatively associated with transfer, especially for Black and Hispanic students.

Overall, perhaps with the exception of the mostly negative effects of part-time faculty, the literature is mostly unclear with respect to the impact institutional and state level variables have on transfer likelihood. This may be due to the use of rather crude aggregate measures, which fail to identify more proximal institutional processes and procedures. For example, if remediation, as it is currently delivered, results in lower odds of transfer, colleges, ostensibly, could change their policies with respect to who is directed to remediation and/or how the purported gap in academic preparation is bridged.

Unfortunately, due to current software limitations vis-à-vis the particular statistical method employed in this dissertation, I am precluded from conducting a multilevel analysis that includes institutional and state level predictors of transfer. However, this is clearly an area for further research.

1.4: Why a Latent Class Model?

Few studies examine differences in community college students that may lead to differences in the relationships between predictors and transfer outcomes. Among the few studies that have examined differential relationships among predictors and transfer outcomes across students, these studies have examined differences on the basis of only one observed variable at a time , e.g., ethnicity (Crisp & Nuñez, 2014). While such studies acknowledge that students who differ with respect to a given observed characteristic may respond differently to the same treatment, it is likely that several observed student variables simultaneously interact with potential treatments.

Latent Class Analysis is one method of modeling the complexity of several potential moderating variables (Lanza & Rhoades, 2013; Lazarsfeld & Henry, 1968; Magidson & Vermunt, 2004; Masyn, 2013; McCutcheon, 1987). Similar to latent factor analysis, latent class analysis posits a categorical latent factor reflected by several observed variables. One of the attractive features of Latent Class Analysis is its ability to cluster individuals, on the basis of their item response patterns, into a smaller number of manageable subtypes, which then can be used to test for potential moderating effects (Cooper & Lanza, 2014; Lanza & Rhoades, 2013). This dissertation appears to be the first to use latent class analysis in the study of community college outcomes in general and four-year transfer in particular. As a result, there is an absence of directly relevant research literature. Nonetheless, I offer three reasons why latent class analysis is an appropriate method to answer my essential research question.

First, while methodologically rather complex, this dissertation essays to offer something of practical use to community colleges charged with the daunting task of drastically increasing the number of students who transfer to four-year institutions. While the research literature is fairly consistent in its identification of the associations between student background characteristics, academic resources, transfer intentions, external demands, academic momentum and probability of four-year transfer, the sheer number of variables and their possible combinations inhibits the feasibility of establishing targeted advising or interventions.

Implicit in this statement is the assumption that neither a one-size-fits all nor a completely individualized approach to advising and interventions is appropriate in the first case or even possible in the second. On the one hand, it is clear that community college students are far from monolithic when it comes to their academic resources, transfer intentions, external demands, etc. (Horn, 2009; Horn & Skomsvold, 2011). On the other hand, for example, given the eight research based variables I selected for the latent class analysis, there are 864 possible response vectors, effectively precluding the creation of any sort of individualized actions plans.

Consequently, the first reason why I chose to use a latent class analysis is to identify a small number of groups in which students are relatively heterogeneous across and homogenous within groups with regard to their positions on the various items that measure the putative constructs I identified from the literature (Collins & Lanza, 2010). If a latent class analysis is successful in revealing an a priori unspecified number of substantively useful latent classes, community college leaders could use the results to provide targeted advice and interventions that address the disparate needs of a small number of transfer student subtypes.

Second, given my interest in identifying clusters of individuals with similar response patterns, I could have selected a more traditional clustering technique, e.g., K-means clustering. However, unlike other cluster analytic methods, latent class analysis is a model based statistical procedure that allows for rigorous statistical testing (Magidson & Vermunt, 2002; Wang & Wang, 2012). Not only are latent classes determined on the basis of posterior membership probabilities, rather than somewhat subjectively reviewed dissimilarity measures in the case of cluster analysis, but there also exists several well-studied fit indices to aid in the decision as to the optimal number of latent classes (Nylund, Asparouhov, & Muthen, 2008). Indeed, Magidson and Vermunt (2002) demonstrated through simulation studies that latent class clustering significantly outperformed the more traditional K-means clustering in terms of both identifying the correct number of classes and accurately classifying cases.

The third reason I chose latent class analysis, rather than other competing clustering methods, is precisely because it is a latent variable model that corrects for measurement error (Collins & Lanza, 2010). Like traditional factor analysis, latent classes are measured by observed indicators, which are *caused* by both the underlying hypothesized latent variable and error. Because latent variable models, like latent class analysis, partition the variance of indicators into that caused by the underlying construct and error, the resulting latent classes are error free. That the latent classes are corrected for error satisfies one of the important assumptions for variables used in my subsequent structural model, thus resulting in increased statistical power (Brown, 2014).

1.5: Goals of this Study

In this dissertation, I use the statistical techniques of latent class analysis (LCA), confirmatory factor analysis (CFA) and structural equation modeling (SEM) to identify potential latent transfer subtypes, account for the unreliability in the indicators of the hypothesized latent student engagement factor, and examine the associations between student background variables, latent class membership, student experiences, academic performance and four-year transfer likelihood. Perhaps, most importantly, this study examines whether latent class membership moderates the relationships between malleable community college student experiences, academic performance, and transfer.

The first primary goal of this study is to assess whether a latent class analysis can identify and classify students, on the basis of their standing on several literature based correlates of transfer, into a small number of meaningful transfer subtypes that are both homogenous within and heterogeneous between classes. Given that latent class analysis has not been applied to the study of community college transfer, the results of this study could present educational researchers with a new method by which to analyze this complex problem.

The second goal of this study is to examine the relationships between student background variables, latent class membership, student experiences, academic performance and transfer likelihood using a relatively new, unbiased 3-step approach to the analysis of both predictors of latent class and latent class prediction of distal outcomes (Asparouhov & Muthén, 2014a; Vermunt, 2010). Methodologically, both predicting latent class membership, and, especially, predicting distal outcomes from the latent classes, without either changing the meaning of the latent class or introducing bias into the structural model, has been difficult. Therefore, in addition to the substantive findings related to the second goal, this study also tests the methodological feasibility of implementing the 3-step approach as applied to the study of transfer.

The final goal of this study, as mentioned above, is to examine whether the relationships between student experiences and academic performance variables and transfer vary across latent transfer subtypes. Specifically, from a substantive perspective, the goal is to assess whether the effects of remediation, academic engagement, and first-year GPA are the same across latent transfer subtypes. If the relationships between these malleable factors and transfer depend on latent transfer subtype, community college leaders could use such information to provide transfer subtype specific advice and/or interventions. In this way, scarce community college resources could be allocated strategically to increase transfer for all students by tailoring interventions to meet the needs of each specific transfer subtype.

1.6: Research Questions

1. (a) Based upon students' statuses with respect to (i) academic resources, (ii) transfer intentions, (iii) external demands, and (iv) academic momentum, can a latent class

analysis identify meaningful transfer subtypes, which are qualitatively distinct across and relatively homogenous within subtype?

(b) Using appropriate fit indices (i.e., *BIC*, *aBIC*, *LMR-LRT*, etc.) and substantive interpretability as guides, what is the optimal number of latent classes that describe the observed response patterns?

(c) How precisely does the resulting latent class model classify students into the transfer subtype latent classes?

(d) Does the latent class model possess measurement invariance (configural, metric/scalar invariance) across Gender, First Generation College Status, and Minority Status?

(e) Are the any direct effects from covariates to latent class indicators?

2. (a) Does a confirmatory factor analysis model support the hypothesis that the NCES academic engagement index—an index based on the average of several Likert-like scaled questions involving frequency of engagement with faculty and the institution—can instead be modeled as a latent factor reflected by the same four indicators?

   (b) Does the latent engagement factor possess measurement invariance (configural, metric/scalar invariance) across Gender, First Generation College Status, and Minority Status?

3. (a) Using the 3-step procedure, does Gender, First Generation College Status, and Minority Status predict latent class membership?

   (b) Does conditional latent Class membership predict first-year GPA, Academic Engagement, Remediation, and Transfer?

   (c) Conditional on latent class membership (i.e., estimating class-specific intercepts) does First-Year GPA, Academic Engagement, and Remediation predict transfer probabilities?

d) Allowing intercepts and slopes to vary across classes, does latent class membership moderate the relationships between, student background, First-Year GPA, Academic Engagement, Remediation and Transfer?

4. Does the use of latent class analysis and the results of the structural models have practical implications for interventions aimed at increasing transfer rates?

1.7. Implications of this Study

The results of this survey will contribute to the scholarly literature on community college transfer in both methodological and substantive ways.

Methodologically, this dissertation appears to be the first to use a latent class measurement model to classify students into transfer subtypes on the basis of their standings on several research-based correlates of transfer. In addition, this study not only incorporates a latent class measurement model, but also utilizes a relatively new, unbiased 3-step approach to examine predictors of latent class as well as latent class prediction of distal outcomes. Therefore, if the latent class measurement and structural models prove insightful, educational researchers who study community college transfer, as well as other outcomes, may have a new method through which to examine an old problem.

Substantively, the results of this study will advance the current understanding of both which initial variables impact community college transfer to four-year institutions and whether these variables have the same effect for different latent transfer subtypes. First, this study will corroborate (or not) earlier findings regarding the role of student background characteristics, academic resources, transfer intentions, external demands, academic momentum, student experiences, academic performance and transfer.

Second, the results of this study will provide a nuanced look at the differential relationships between remediation, first-year GPA, engagement and transfer across latent transfer subtypes. If the relationships between the above mentioned malleable variables and transfer vary by latent transfer subtype, community colleges could design latent transfer subtype-specific interventions. Ultimately, in practice, community colleges could classify students, on the basis of an upfront assessment, into one of the transfer subtype latent classes. Second, based on the results of this study, community colleges could then provide class-specific advice and interventions, rather than a one size fits all approach, which may or may not be right for each transfer subtype. In this way, community colleges may increase transfer rates in an efficient manner that meets the needs of its diverse student population.

Moreover, given the significant role that community colleges have in the national college completion agenda, this study could offer methodologically sound advice to community college systems who seek to increase student transfer rates (Harbour & Smith, 2015; Lester, 2014; Teranishi & Bezbatchenko, 2015). Further, unlike many transfer studies based on single institutions or convenience samples, this study utilizes nationally representative datasets, thus providing a high degree of external validity.

In addition to this study's potential to uncover malleable variables related to transfer, it also applies a latent class analysis approach to modeling potential transfer subtypes of community college students. The resulting transfer subtypes could be used to create more targeted interventions, which could, in turn, provide more strategic direction to colleges as to how best to spend already scarce resources.

Methodologically, this study represents a fairly complex application of the new three step modeling approach, including several covariates, an additional latent factor, and several categorical distal outcomes, including four-year transfer.

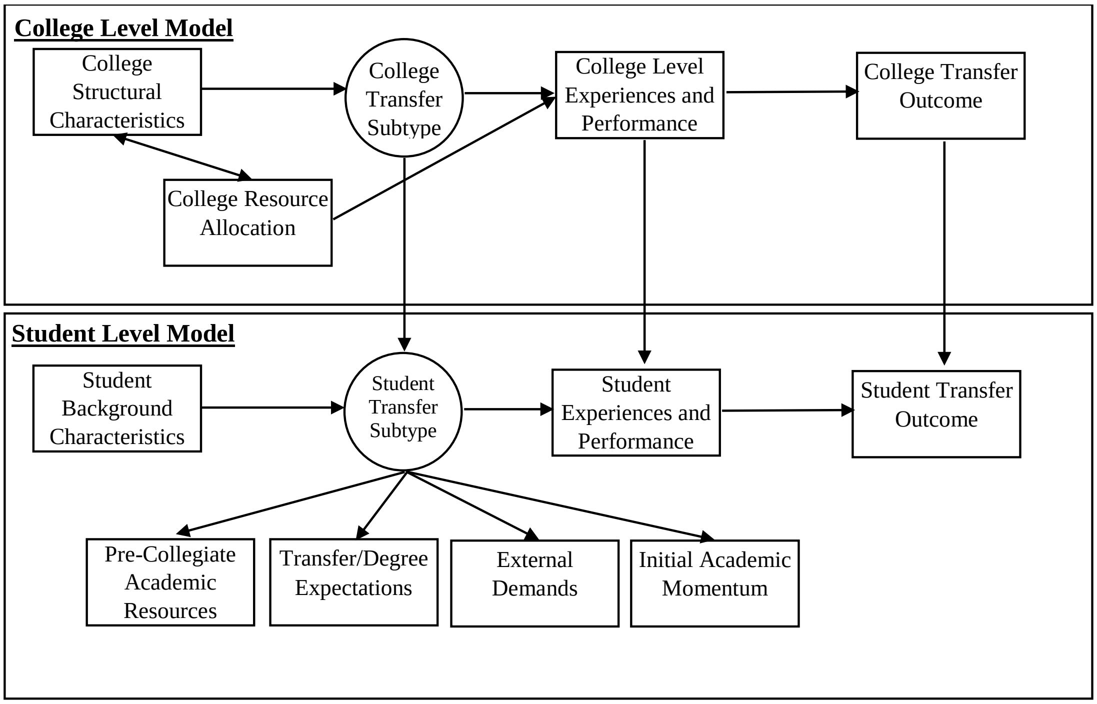
Finally, community colleges, like all public agencies, fall under the scrutiny of several state and federal accountability systems; college transfer rates are almost always at the top of the list of accountability outcomes. This study could offer a new means of “leveling the playing ground” before comparing transfer rates between colleges (Hom, 2009; Riley Bahr, Hom, & Perry, 2005). In other words, community college systems could compare transfer rates of similar transfer subtypes across colleges, rather than comparing overall transfer rates between colleges, which surely vary in the prevalence of each hypothesized transfer subtypes.

In sum, beyond the potential methodological advances, the findings of this study will provide important, actionable information for college administrators and state policy makers seeking to increase transfer rates to four-year institutions. Both the methodological and substantive findings of this study come at a time when community colleges are being called upon by Washington to significantly increase the number of community college graduates and transfers to four-year colleges. The findings of this study have the potential to significantly advance our current understanding of transfer as well as to provide specific suggestions as to how the country might meet identified targets for transfer and student completion (Handel, 2013).

CHAPTER 2: LITERATURE REVIEW

The conceptual model displayed in Figure 1 represents the theoretical/empirical framework for this dissertation.

Figure 1. *Conceptual Model of Community College Transfer*



This model is based on prior models of community college transfer that suggested that student background characteristics influence high school academic performance, which, in conjunction with external demands, shape degree aspirations and transfer intentions, all of which influence academic momentum, academic engagement, the need for remediation, and academic performance, which, in addition to institutional level characteristics and processes, ultimately predict the likelihood of four-year transfer (Lee & Frank, 1990; Nora & Rendon, 1990; Wang, 2009).

However, while my conceptual model incorporates similar constructs, it diverges from past empirical models in both the measurement of and structural connections between constructs. Similar to previous models, my conceptual model begins with the least malleable variables, student background characteristics, which, different from previous models, I posit, influence a latent categorical variable that is measured by the slightly more malleable domains of academic resources, degree aspirations/transfer intentions, external demands, and academic momentum. Next, my conceptual model hypothesizes that student characteristics, latent class membership, and the most malleable variables, student experiences and academic performance, predict transfer outcomes. Finally, though not displayed explicitly, the model hypothesizes that latent class membership moderates the relationships between student background variables, student experiences, academic performance and transfer.

At the institutional level, the conceptual model hypothesizes that community college structural characteristics are correlated with college resource allocations, which influence college level experiences and academic performance. Moreover, the model postulates that college structural characteristics influence transfer subtype latent class prevalence, which in turn affect college level experiences, academic performance and college level transfer rates.

Unfortunately, at the time of this dissertation, limitations in available software precluded the use of the improved three-step analysis of a multilevel latent class structural equation model. Therefore, this study only considers the student level model presented in Figure 1.

Although conceiving the path to transfer as following a strictly linear or hierarchical trajectory would be an oversimplification for many students, the transfer literature, in general, characterizes the ascent to transfer as a quasi-linear voyage set in motion by pre-college student background characteristics and associated academic resources, further influenced by external demands, which in turn shape degree expectations, college program choices, initial academic momentum, student engagement, the need for remediation, academic performance and ultimately a student's probability of four-year transfer. At the same time, institutional and statewide characteristics, processes and policies may also affect student transfer outcomes.

Chapter 2 reviews in greater detail the substantive transfer literature introduced in Chapter 1. The conceptual model displayed in Figure 1 provides an organizing framework for this review, which is divided into (i) student and (ii) institutional/state correlates of community college transfer to four-year institutions. Because of the relative dearth of transfer studies that have considered institutional/state variables and because this dissertation only includes student level variables, I spend considerably more time discussing student level correlates of transfer.

2.1: Student Level Variables Associated with Transfer

Reading from left to right, the conceptual model displayed in Figure 1 begins with the least malleable factors—student background characteristics—and ends with, ostensibly, the most malleable of the variables—student experiences and academic performance. Therefore, following this pattern, this section of the literature review will discuss the associations among the following student level domains and four-year transfer likelihood:

(i) Student Background Characteristics

(ii) Pre-Collegiate Academic Resources

(iii) Transfer Intentions/Degree Expectations

(iv) External Demands

(v) Initial Academic Momentum

(vi) Student Experiences and Outcomes

2.1.1 Student Background Characteristics.

Typically employed as statistical controls, several studies have corroborated the direct and indirect associations among several student background characteristics and the probability of transferring from community colleges to four-year institutions. Furthermore, because of the significant role community colleges have played in the democratization of postsecondary access, a significant amount of research has focused on assessing the degree to which community colleges serve to mitigate or simply reproduce social and economic inequalities (Dickert-Conlin & Rubenstein, 2007; Dougherty & Kienzl, 2006; Dowd, 2003; Lucas, 2001; Pfeffer, 2008; Schudde & Goldrick-Rab, 2014).

On the one hand, community colleges increase access for students who are unable to attend four-year institutions due to poor academic achievement in high school, financial concerns, family obligations, proximity, etc. To this point, in most states, students may attend community colleges without having graduated from high school, with little to no tuition costs, and flexible schedules wherein students may attend part-time, in the evenings, or most recently, virtually through web-based distance education modalities (Cohen et al., 2013).

On the other hand, Schudde and Goldrick-Rab (2014) point out that, while community colleges increase postsecondary access, which is ultimately positive, students who attend community colleges, compared to those who attend four-year institutions, are much more likely to come from lower income families, to be first-generation college students, and/or from underrepresented racial/ethnic groups. Consequently, while access is increased by community colleges, four and two year colleges are stratified such that community colleges are disproportionately accessed by the least privileged, and four-year colleges by the most privileged. Because the payoff associated with attending a four-year institution is greater than that of attending a two-year community college, unless community college students are able to transfer to four-year institutions, it could be argued that community colleges often reproduce rather than ameliorate social inequality (Brint & Karabel, 1989; Dougherty & Kienzl, 2006).

With respect to privilege, resources, social and human capital, as is well established in nearly every study of academic achievement, socioeconomic status (SES) is highly correlated with the likelihood of four-year transfer (Bradburn et al., 2001; Dougherty & Kienzl, 2006; Dowd, Cheslock, & Melguizo, 2008; Dowd, 2008; Ishitani, 2006; Kalogrides & University of California, 2008; Knoell & Medsker, 1965; Lee & Frank, 1990; Nora & Rendon, 1990; Velez & Javalgi, 1987; Wang, 2012). Constructed as a composite or latent variable based, in most cases, on parental educational attainment, income level, occupational prestige, and sometimes wealth, students from lower SES backgrounds, all things being equal, are significantly less likely to transfer than are students from moderate or high SES backgrounds.

While studies indicate that the direct impact of SES on transfer is attenuated by the inclusion of relevant mediating variables, its direct and indirect impact on the probability of transferring remains, nevertheless, statistically and practically significant (Dougherty & Kienzl, 2006; Dowd et al., 2008; Dowd, 2008).

In one of the earliest community college transfer studies, Velez and Javalgi (1987) considered the influence of parental SES on four-year transfer likelihood using the National Survey of the High School Class of 1972 (NLS72). After controlling for student demographics (i.e., gender, race/ethnicity, and religion), high school grades and curricular rigor, encouragement from parents and friends, occupational expectations, college grades, etc., SES remained a significant predictor of transfer. Similarly, Lee and Frank (1990), in another early transfer study, employed path analysis to assess the direct and indirect effects of SES on four-year transfer likelihood. While much of the effect of SES on likelihood of transfer was transmitted indirectly through its effects on high school academic achievement and subsequent college behaviors and achievement, the direct effects of SES on four-year transfer probability again remained statistically significant.

More recently, Dougherty and Kienzl (2006), analyzing data from both the NELS:88 and BPS:90, also found that, while the effects of SES on likelihood of four-year transfer were attenuated by inclusion of several mediating variables (e.g., educational aspirations, external demands, enrollment status, etc.), students from lower SES backgrounds were significantly less likely to transfer to four-year institutions.

In addition to the lingering effects of SES on likelihood of transfer, several studies—including many of those mentioned above—have demonstrated associations among gender, ethnicity and likelihood of four-year transfer (Freeman, 2007; Hungar & Lieberman, 2001; Jones-White, Radcliffe, Huesman, & Kellogg; Lee & Frank, 1990; Nora & Rendon, 1990; Velez & Javalgi, 1987). With respect to gender, initial studies conducted in the 1980s and early 1990s generally found that females were less likely to transfer than males (Lee & Frank, 1990; Velez & Javalgi, 1987). Similarly, these and other early studies also found that transfer rates for Black and Hispanic students were consistently lower than for White and Asian students (Grubb, 1991).

However, more recent studies conducted since the year 2000 have revealed that the direct effects of gender and race/ethnicity on transfer, when conditioned on SES, pre-college academic achievement, and other significant college experience and external demand variables, either cease to be statistically significant, or if significant, their effect sizes are greatly attenuated (Dougherty & Kienzl, 2006; Horn, 2009; Roksa, 2006).

Conversely, and contrary to other more recent studies, Wang (2012), analyzing the National Education Longitudinal Study of 1988 (NELS: 88/2000) and the Postsecondary Education Transcript Study (PETS), found that Black community college students were 23.4% less likely to transfer than their White counterparts, even after controlling for SES, academic preparation, several psychological variables, and other college behaviors. Interestingly, Dougherty and Townsend (2006) found that Black students, who were similar to White students with respect to SES, had significantly higher degree aspirations, which acted to suppress the effect of being Black on transfer likelihood. However, because Wang (2012) restricted his sample to only those students with high degree aspirations, the negative association between being Black and transfer was not suppressed by variation in degree aspirations.

Overall, examining the associations among student background characteristics and the probability of transfer is critically important because, first, these characteristics are immutable, and, second, if the very students who are most likely to attend community colleges are the most unlikely to transfer, community colleges, rather than reducing social inequality, may as critics contend, simply reproduce inequality.

2.1.2: Pre-Collegiate Academic Resources

In addition to student background variables, the transfer literature also has established the significant association between pre-collegiate academic resources and the probability of four-year transfer (Adelman, 2006; Bradburn et al., 2001; Dougherty & Kienzl, 2006; Kalogrides & University of California, 2008; Lee & Frank, 1990; Long & Kurlaender, 2009; Nora & Rendon, 1990; Porchea et al., 2010; Velez & Javalgi, 1987; Wang, 2012).

In general, students who complete more rigorous high school curricula, obtain AP credits, or complete college classes while in high school (particularly with respect to mathematics), achieve greater overall high school grade point averages, and score higher on pre-college standardized tests are significantly more likely to transfer to four-year institutions (Allen, Robbins, Casillas, & Oh, 2008; Dougherty & Kienzl, 2006).

For example, Dougherty and Kienzl (2006), in one of the most comprehensive community college studies using the National Education Longitudinal Study(NELS:88), found that, conditional on social background, race/ethnicity, educational aspirations, external demands, college experiences, remediation, and several other correlates of transfer, 12^{th}-grade math test score was the strongest predictor of transfer. Similarly, Lee and Frank (1990), in one of the earliest transfer studies, found that curriculum rigor as well as the number of math classes taken, were statistically significantly associated transfer outcomes.

In another study of community college transfer among Florida community college students who were deemed unprepared for college on the basis of initial placement tests, Roksa and Calcagno (2008) found a strong relationship between merely taking the SAT/ACT and the odds of transfer. Because their study failed to account for degree expectations, it is unclear, however, whether taking the SAT/ACT signaled interest in four-year transfer or whether this signaled an academic resource that was undetected by the incoming placement exam.

In addition, unlike most four-year institutions, as mentioned above, possession of a high school diploma is not required, in most cases, to enroll in a community college. For example, more than 10% of first-time community college students represented in the 2003-04 beginning postsecondary education survey did not have a high school diploma (BPS: 2003-04).

With respect to four-year transfer, community college students who lack this academic resource—a high school diploma—are generally less likely to transfer to four-year institutions than students who have a high school diploma (BPS 2003-04). Nonetheless, once conditioned on other academic achievement indicators, degree aspirations, etc., Dougherty and Kienzl (2006), for example, found that possession of a high school diploma was not a statistically significant predictor of four-year transfer.

2.1.3: Transfer Intentions/Degree Expectations

As one would expect, students' degree expectations are strongly associated with four-year transfer likelihood (Adelman, 1999, 2005a, 2006; Alfonso, 2006; Alfonso, Bailey, & Scott, 2005; Bradburn et al., 2001; Laanan, 2003; Porchea et al., 2010). For example, Adelman (2006) found that community college entrants who aspired to attain a baccalaureate degree or higher, conditional on SES, high school academic performance, race/ethnicity, as well as several other college behaviors and experiences, were 24% more likely to transfer to a four-year institution than students with the lowest educational aspirations.

With respect to educational aspirations, Messersmith and Schulenberg (2008); Wang (2013) note that educational *aspirations* differ from educational *expectations*. Specifically, educational *aspirations* reflect a student's desired educational outcome without regard to external constraints, whereas educational *expectations* reflect a student's desired educational outcome after taking into account external constraints. For example, a student may aspire to complete a Master's degree, but, after assessing the potential costs and available resources, the student may reduce educational *expectations* to only baccalaureate degree completion. Conversely, and presumably occurring with less frequency, a student may have higher educational *expectations* than *aspirations* as a result of external forces. For instance, imagine a student who aspires to complete only a baccalaureate degree, but in order to maintain her job, she must complete a Master's degree, which compels her to increase her educational expectations above her initial aspirations.

Generally, educational expectations, regardless of sector, have been tied to educational attainment. For example, Sewell, Haller, and Portes (1969), explain the role of educational expectations in educational attainment from the perspective of the status attainment model. Essentially, they argue that students' family background and cognitive abilities influence both academic performance and the specific advice they receive regarding educational paths. Subsequently, both academic performance and the educational advice received shape education expectations, which largely determine educational attainment (Sewell, Haller, & Ohlendorf, 1970). Similarly, though from the perspective of educational psychology, Eccles and Wigfield (2002) demonstrate the impact educational expectations have on students beliefs, motivation and ultimately behavior, which in turn are related to educational attainment.

Though its salience in predicting transfer may appear tautological, some disagreement exists in the literature as to whether researchers should include degree expectations in their models or rather limit their analyses to include only students who intend to transfer. (cf: Bradburn et al., 2001; Spicer & Armstrong, 1996; Velez & Javalgi, 1987; Wang, 2012). With respect to accountability reports prepared for legislative bodies (that also happen to decide community college funding levels), researchers typically only report the transfer rates of students who have baccalaureate (or higher) degree expectations and/or *behave* as if they intend to transfer (Riley Bahr et al., 2005).

Although there may be compelling reasons to exclude students with non-transfer oriented educational aspirations, doing so presents at least two problems for studies that essay to model the probability of transfer. First, both Spicer and Armstrong (1996) and Bradburn et al. (2001) demonstrated that employing increasingly restrictive definitions of who qualifies as a transfer-intended student not only reduces the sample size, as well as external validity, but also fails to account for all students who actually do transfer. In other words, while the probability of transfer is greater for students who aspire to transfer, many students with occupational or other non-transfer goals also transfer to four-year institutions. Indeed, nearly 13% of 2003/04 beginning community college students with non-transfer goals, transferred to a four-year institution within six years (NCES Powerstats).

Second, the opposite problem also exists: namely, limiting the study to transfer-intended students assumes that measures of transfer-intention are perfectly reliable, when, in fact, some students, who indicate they desire a baccalaureate degree or even behave as if they are pursuing said degree, are actually intent on pursuing a different educational goal. For example, as previously mentioned, roughly 82% of 2003-04 community college beginners indicated postsecondary degree expectations of baccalaureate degree or higher (BPS: 2004)—an expectation that categorically requires upward transfer. However, when the same students were asked about their specific educational plans at the sample community college, less than 60% indicated plans of four-year transfer.

Related to this discussion, researchers continue to debate the role community colleges play in shaping students' degree expectations. On the one hand, Clark (1960, 1980) proposed that community colleges—specifically, academic counselors—effectively *cool out* students whose degree aspirations exceed their perceived abilities. Instead, Clark (1960) maintains, academic counselors divert students away from baccalaureate (or higher) degree aspirations and toward more *realistic* educational goals (e.g., vocational degrees, certificates, etc.), which, from the academic counselor's assessment, are better aligned with students' abilities.

On the other hand, for example, Bahr (2008a) found that exposure to community college academic counselors actually increased students' likelihood of achieving their stated educational aspirations. Similarly, Alexander, Bozick, and Entwisle (2008) suggest that community college attendance may actually *warm up* some students' degree aspirations. Regardless of whether community colleges serve as *coolers* or *warmers*, the agreed upon notion that community colleges have the potential to exert such influence, highlights the fact that degree aspirations are not only subject to measurement error, but also conceived as potentially malleable.

Because transfer expectations and degree aspirations are not directly observable, and subject to measurement error, a latent treatment of this important variable, as modeled in this study, may provide a clearer picture of students' true transfer intentions and degree expectations.

2.1.4: External Demands

Compared to four-year college students, community college students have significantly greater external demands. For example, related in part to the fact that community college students tend to begin college at an older age than four-year beginners, according to the most recent Beginning Post-Secondary Education Survey (BPS:04/09), 37% of 2003/04 first-time public two-year community college students were financially independent compared to only 7.5% of public four-year college beginners. Moreover, the same survey showed that nearly 12% of first-time community college students were single parents, compared to only 2.2% of public four-year college beginners (Skomsvold et al., 2011). Likewise, again from the BPS:04/09, 30.9% of community college students worked full-time (≥35 hours/week) in 2003/04 compared to only 8.6% of public four-year beginners (Skomsvold et al., 2011).

First, as mentioned in the previous section, external demands may reduce degree expectations and transfer intentions. Indeed, students who are financially independent, work full-time, or have dependents, with or without being married, are less likely to indicate four-year transfer as a goal than dependent students who do not work full-time (NCES Powerstats). Essentially, external demands may prompt students to settle for educational expectations that do not necessarily match their unconstrained educational aspirations (Wang, 2013).

In addition to downgrading educational expectations, in general, external demands (also referred to as environmental pull) negatively affect academic momentum, engagement, and community college academic performance, which in turn reduce the probability of four-year transfer (Adelman, 1999, 2005a, 2006; Crisp & Nuñez, 2014; Dougherty & Kienzl, 2006; Nora, 2004). Several studies indicate that students who are financially independent, married, have dependents, and/or work full-time have lower four-year transfer probabilities than students without these external demands (Bradburn et al., 2001; Dougherty & Kienzl, 2006; Kalogrides & University of California, 2008; Lee & Frank, 1990; Smith & Miller, 2009; Velez & Javalgi, 1987; Wang, 2012).

In essence, external demands and college demands compete for, presumably, finite resources such as time and energy, which are prioritized and allocated according to intrinsically and extrinsically influenced levels of commitment (Bahr, Toth, Thirolf, & Massé, 2013; Nora, 2004). For example, students who work full-time (i.e., 35 or more hours per week) or have children may find it difficult to enroll full-time, devote the necessary time to complete assignments, engage with faculty outside of class, join social clubs, etc, thereby slowing academic momentum, and reducing academic achievement and engagement.

While external demands tend to reduce community college students' probability of transferring to a four-year institution, some studies suggest that financial support, particularly in the form of grants, may ameliorate some of the deleterious effects associated with external demands (Adelman, 2005a; Nora & Rendon, 1990). However, some studies suggest that financial support in the form of loans may have the opposite effect on community college outcomes. For example, Kim (2007) found that accruing higher loan debt in the first year of college was associated with lower rates of degree completion especially for low income or Black students.

2.1.5: Initial Academic Momentum

As prefatory, Adelman's (1999, 2005a, 2006) theory of academic momentum asserts that the velocity with which students begin their college careers is associated with greater probabilities of subsequent degree and/or transfer outcomes. According to the theory, a student's potential for momentum begins even before postsecondary enrollment through the accumulation of college credits earned in high school, followed by immediate postsecondary enrollment (no delay) after high school. To continue academic momentum at the postsecondary institution, Adelman (1999) demonstrates the importance of initial academic intensity in the forms of full-time enrollment and accumulation of credits, particularly during the first term and year.

As mentioned, academic momentum has the potential to start while students are still in high school. Students who earn college credits in high school reap several academic benefits. For example, Allen and Dadgar (2012) found that, after controlling for several student background and pre-collegiate academic achievement variables, students who earned college credit while in high school reduced their time to degree, and achieved higher grade point averages than students who did not earn college credit while in high school.

Continued momentum is achieved by enrolling in college immediately following high school graduation. Community college students are more likely to delay postsecondary enrollment than their four-year counterparts. For example, among beginning postsecondary students in 2003/04, 47.6% of community college beginners, compared to only 15.1% of four-year beginners, delayed postsecondary enrollment for at least one year after high school (Karp, Hughes, & O'Gara, 2010; Smith & Miller, 2009). Delaying enrollment for most students (and all students over 24 years of age) is, for all intents and purposes, synonymous with financial independence (Adelman, 2005a), which is negatively related to transfer outcomes.

Moreover, many students who delay postsecondary enrollment also are married with or without dependents, single with dependents, working full-time or any combination thereof (Dougherty & Kienzl, 2006). It is somewhat unclear, however, whether students delay enrollment for the purpose of working or raising a family or whether, because they delayed enrollment due to low academic achievement in high school and/or low educational expectations, etc., they are more likely to be working full-time, raising a family, etc.

Regardless of the underlying cause of the delay, Dougherty and Kienzl (2006) found that, after controlling for other demographic variables, degree expectations, enrollment intensity, etc., community college students who were between the ages of 21 and 30 when first enrolled were 15% less likely to transfer than students who were under 21 years of age at the time of first enrollment. Similarly, students who were 31 years of age and older were 20% less likely to transfer than community college beginners under the age of 21.

In addition to the deleterious effects of delayed entry on four-year transfer probability, several transfer studies also have confirmed the strong association between initial enrollment intensity and transfer (Adelman, 2005a, 2006; Attewell et al., 2012; Doyle, 2011). While momentum is maximized by completing credits, several studies confirm that simply attempting a full-time credit load in the first term is associated with higher odds of transfer (Attewell et al., 2012). Indicative of the presumed importance of full-time enrollment status, many community college accountability measures that assess transfer performance limit their analyses to include only those students who enroll full-time in their first semester. For example, the Student Right-to-Know and Campus Security Act, which amended education law in 1999, requires all community colleges (and other Title IV eligible postsecondary institutions) to report transfer rates among first-time, full-time students.(Bailey, Calcagno, Jenkins, Leinbach, & Kienzl, 2006; Bailey, Crosta, & Jenkins, 2006).

In a methodologically robust study, Attewell et al. (2012), using a growth curve modeling approach, found that initial credit loads statistically significantly predicted students' later credit accumulation trajectories. Based upon the significant association between the intercept (initial status) and slope (credit accumulation trajectory) in the multilevel growth model, Attewell et al. (2012) then employed propensity score matching to examine the effects of initial academic momentum on the probability of associate degree or higher attainment. After matching treatment groups on nearly 70 covariates, the probability of associate degree or higher completion for community college students enrolled full-time in their first term was between 8 and 13 percentage points greater than for students enrolled in fewer than 12 units during their first term.

In addition to enrolling full-time, completing a threshold number of units in the first year of enrollment is also associated with transfer outcomes. For example, Doyle (2011), using a generalized propensity score approach (matching treatment groups on 45 covariates), estimated predicted transfer rates of 39% for students who completed at least 30 credit hours in their first year, compared to only 26% for students who completed between 12 and 23 credit hours in the same timeframe. Similarly, Moore, Offenstein, and Shulock (2009) in a study of California Community college students, found that 63.8% of students who completed 20 units in their first year eventually became transfer prepared (met all requirements for transfer), compared to only 28.9% of students who completed fewer than 20 units. Similarly, Leinbach and Jenkins (2008) showed that 55.8% of community college students who completed 15 college level units in their first term, transferred or received a degree compared to 36.5% of students who took two years to reach this milestone.

2.1.6: Student Experiences and Academic Performance

For the majority of community college beginners, many of the same behaviors, experiences and outcomes that predict associate degree completion also predict transfer success (Adelman, 2005a, 2006; Bahr, 2009; Calcagno et al., 2007; Lee et al., 1993; Pascarella, Smart, & Ethington, 1986; Porchea et al., 2010; Robinson, 2004; Stratton, O'Toole, & Wetzel, 2007; Taniguchi & Kaufman, 2005). With few exceptions, the path to transfer requires students to collect several of the same enrollment milestones with similar levels of academic achievement (e.g., grade point averages) as students on the path to degree completion (Adelman, 2005a, 2006; Pascarella et al., 1986; Wang, 2012). For example, to be successful in either case, students must receive passing grades in required coursework, accumulate credit units, persist from term to term, and obviously not drop-out of college.

Related to academic performance, the association between student academic and social engagement (or integration or involvement to be discussed) and college outcomes, at least at four-year institutions, has been well established (Astin, 1999; Kuh, 2003; Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008; Pascarella & Terenzini, 1991; Pascarella, Terenzini, & Feldman, 2005; Tinto, 1987). However, the role engagement plays in community college student outcomes is unclear (Deil-Amen, 2011; Nora, 2004). Some studies show that engagement is positively related to community college outcomes (McClenney, Marti, & Adkins, 2012), while other more rigorously controlled studies concerned specifically with transfer outcomes fail to find a significant relation between the two (Dougherty & Kienzl, 2006; LaSota, 2013).

Finally, this section spends considerable time on the topic of remediation. Increasingly, studies point to the negative relationship between remediation and transfer (Crisp & Delgado, 2014; Dougherty & Kienzl, 2006; LaSota, 2013; Moore et al., 2009). However, other studies find positive or neutral effects of remediation on transfer odds at least for some students (Bahr, 2008b; Calcagno et al., 2007).

Student Experiences and Academic Performance are important variables because they are viewed as malleable. From the perspective of community colleges, that these variables are potentially malleable means there may be additional activities (e.g., tutoring, supplemental instruction, opportunities for enhanced engagement) that could be implemented or policies changed (e.g. changing how and who is assigned to remediation), which could significantly affect transfer rates.

2.1.7: Academic Performance

Numerous studies indicate that community college academic performance—

especially early on—is positively associated with degree completion, transfer to 4-year institutions and eventual baccalaureate attainment (Adelman, 1999, 2005a, 2006; Adelman, Daniel, Berkovits, & Owings, 2003; Pascarella et al., 1986; Terenzini, Springer, Yaeger, Pascarella, & Nora, 1996; Velez & Javalgi, 1987)., Indicators of community college academic achievement include first-year college grade point average, number of course withdrawals or repeats, completion of required gatekeeper courses, and accumulation of transferable units as well as credentials (Associate Degree or Certificate, etc.).

With respect to first-year grade point average, Crisp and Nuñez (2014) found that, in separate analyses of white and underrepresented minority students, controlling for pre-college factors, external demands, degree expectations, academic integration as well as institutional level variables, first-year GPA was statistically significantly related to the odds of transfer. Similarly, LaSota (2013) after controlling for an impressive number and type of student, institutional and state level variables, found that with every .10 increase in first-year GPA, the odds of transfer increased by 60%. However, her model did not take into account pre-collegiate academic performance, which may explain the magnitude of the effect size.

Related to academic achievement, but not reflected by a student's GPA, increased numbers of no-penalty withdrawals and repeats are also associated with lower degree and transfer rates (Adelman, 2005a). The choice to withdraw may signal academic difficulty or be related to changes in external demands, but in either case, Adelman (2005a) notes that the result is a decrease in academic momentum, which is negatively associated with transfer and degree completion.

2.1.8: Student Engagement

To begin, the research literature discusses three distinct, but similar concepts that I refer to globally as engagement. The first concept, *integration*, attributed to Tinto (1975), represents the degree to which students integrate with the academic and social environments of colleges. Essentially, both academic and social integration reflect how connected students are to the academic and social fabric of the institution. Academic integration is often measured in terms of students' feelings about the quality and frequencies of connections with faculty and other academic agents outside of class. Social integration, while often blurred with academic integration, refers to the social connectedness and fit students have with other students and faculty in social settings.

Similar to integration, Astin (1999) offered the concept of *involvement*, which captures how involved students are with the academic and social facets of the college. Involvement is measured by behaviors that indicate the degree to which their limited time is allotted to academic and social functions, rather than other competing external demands. For example, involvement could be reflected by the number of hours studying per day, or the number of college club meetings attended per month, etc.

Finally, *engagement* is similar to involvement in its emphasis on behaviors, but is limited to those behaviors that are correlated specifically with learning outcomes (Bahr et al., 2013; Marti, 2004). As conceptualized by the Community College Survey of Student Engagement (CCSSE), which nearly 700 community colleges across the United States have administered, engagement is a multidimensional construct consisting of four factors: student effort, academic challenge, active and collaborative learning, student-faculty interactions, and support for learners.

Although each of these concepts capture something slightly different, I choose the word engagement because it is well known, though perhaps not well understood, among community college leaders. In this study, I use four indicators that NCES uses to create what they call an academic integration index. These indicators represent the frequency of interactions with faculty and advisors outside of class in both social and academic settings, as well as the frequency with which students participate in study groups with other students. Technically, based on the definitions above, these indicators seem more in line with the concept of *involvement*, yet they tap into at least two of the domains of engagement. In sum, again, I use the term engagement, because of its familiarity in the community college vernacular, and because the degree to which a student is *engaged* with the institution seems to capture the essence of the construct.

That said, students with higher levels of student engagement generally have higher likelihoods of transfer, though the literature is somewhat mixed on this topic. On the one hand, some studies suggest that students who are engaged with faculty outside of class, participate in study groups, meet with advisors, etc. are, in general, more likely to transfer (Deil-Amen, 2011; LaSota, 2013; Lee & Frank, 1990; Quaye & Harper, 2014). On the other hand, other studies find less support for the relationship between engagement and the odds of transfer (Crisp & Nora, 2010); LaSota (2013); (Nora, 2004). Overall, the results of this study may help to elucidate the association between engagement and transfer.

2.1.9: Remediation

The role of remediation in facilitating positive postsecondary educational outcomes in general and community college degree completion and transfer in particular is highly debated (Adelman, 1999; Jones, 2012; Rose, 2011; Schneider & Yin, 2012). Generally speaking, the research literature is mostly negative with respect to the role remediation plays in postsecondary outcomes. For example, Calcagno et al. (2007), using a discrete time hazard model, found that community college remediation decreased the conditional probability of graduating for all students, especially younger students. Similarly, Wang

(2009) found that, while reading remediation was neither negatively nor positively associated with community college student transfer and baccalaureate degree completion, math remediation was associated with a nearly 20% decrease in the conditional probability of degree completion. Finally, LaSota (2013) analyzing transfer likelihood using the nationally representative BPS: 04/09 survey, found that the odds of transfer for students exposed to remediation, compared to those not exposed to remediation, were reduced by 29%.

However, not all of these studies rigorously controlled for students' high school academic performance. Without such controls, it is unclear whether exposure to remediation is responsible for the reduced likelihood of transfer or whether remediation serves as a proxy for low academic resources carried forward from high school. One notable study that does account for students' high school GPA, highest math course taken, college units earned in high school, as well as several other salient covariates, was conducted by Crisp and Delgado (2014). Using a propensity score matching approach, the authors compared the effect of remediation on the odds of transfer for the matched groups, using a hierarchical generalized linear modelling approach. The results showed that, even after matching students on the aforementioned variables, the odds of transfer were 31.6% lower for students exposed to any remediation coursework than for similar students who were not exposed to remediation. Similar differences in odds were found regardless of the subject in which the remediation occurred.

Conversely, for example, Bahr (2008b), found that among California community college students who successfully passed remedial math courses and continued on to transferable math courses, the odds of transferring or obtaining a degree were equivalent to their non-remediated counterparts.

However, not unlike the previously mentioned studies, most studies that find a positive or neutral effect of remediation on student outcomes only compare outcomes between non-remediated and remediated students who successfully complete the sequence of remediation. Other studies suggest that, while remediation may not have deleterious effects for the relatively few students who successfully complete remediation sequences, most students never transcend remedial course sequences and therefore neither graduate nor transfer (Jones, 2012; Rose, 2011).

Still, other studies not limited to only those students who complete remedial sequences, Bettinger and Long (2005) found no ill-effects of remediation on the odds of transfer. In fact, their results indicated that math remediation may actual increase the probability of transfer. Further, In a later study by the same authors, using a regression discontinuity approach to account for endogeneity of remediation exposure, found that remediation increased first year persistence and credits accumulated, but failed to increase completion rates of college level courses or eventual degree completion rates (Calcagno & Long, 2008).

There is growing evidence that the high stakes placement exams used in most community colleges to sort students into college level or remedial coursework have high specificity but low sensitivity (Scott-Clayton, Crosta, & Belfield, 2014). That is to say, many more students are incorrectly directed to remediation than are incorrectly assigned to college level coursework. For example, Belfield and Crosta (2012), examining two of the most commonly used community college placement exams, found that English misplacement rates based on existing cut scores were between 27% and 33%; the misplacement rates were lower for math, but still significant. Moreover, the authors found that once high school GPA was added to the regression equation, the correlations between test score and course success disappeared. Instead, high school GPA was a much better predictor of course success, resulting in a significant reduction in remediation assignment, without a reduction in successful course completions (Belfield & Crosta, 2012).

Corroborating these findings, researchers at Long Beach City College, a large urban community college in California, recently implemented a student transcript enhanced placement process for all local graduating high school students. Known as STEPS (Student Transcript Enhanced Placement Study), the study revealed that, by using high school transcript information, the percentage of students directed to remediation dropped substantially without concomitant drops in course success. For example, before the use of high school transcript information, only 13% of local high school graduates placed into transferable English courses, whereas, 60% of students placed into transferable English under the new transcript-based placement process. Even more impressive, successful course completion rates were similar to those before the new placement process (64% before compared to 62% after). Though the changes were not as dramatic in mathematics, 30% placed into transferable math under the new system, compared to only 9% previously; success rates in transferable math decreased nominally from 55% before transcript enhanced placement to 51% after its implementation (Willett, 2013).

Clearly, remediation is an area of continued debate, with mounting evidence that it may do more harm than good. If students assigned to remedial courses could have succeeded in transferable courses, as the study above suggests, then there appears to be little benefit with respect to completion milestones, credentials and vertical transfer, even if students develop their skills while in remedial courses. Instead, remediation may simply result in more time at the community college, which is associated with lower probabilities of transfer and degree completion (Jones, 2012).

2.2: Institutional Level Variables associated with Transfer

As outlined above, the research literature has identified several student level variables associated with transfer from community colleges to four-year institutions. In addition, while not as robust as the literature on student-level correlates of transfer, some studies have begun to identify institutional level characteristics, processes or policies—some of which are under the control of community college officials—that are related to student transfer outcomes (Calcagno et al., 2008; Chen, 2012; Crow, 2009; Goble, Rosenbaum, & Stephan, 2008; Mullin, 2012; Wassmer et al., 2004).

In this brief review, three broad categories of institutional level variables will be examined:

(i) Institutional Characteristics

(ii) Student Compositional Characteristics

(iii) Faculty

(iv) Finances

2.2.1: Institutional Characteristics

Typically employed as controls, several relatively fixed institutional characteristics (urbanicity, sector, control, selectivity, size, location, state, etc.) have been linked to retention and degree completion at four-year institutions (Chen, 2012; Lee, 2007; Lee, Song, & Cai, 2010). Clearly, many of these institutional characteristics are irrelevant to community colleges, e.g. selectivity, control, etc.. However it is unclear whether size, location, level of urbanicity, etc. hold the same relationships at community colleges as they do at four-year institutions.

Of the few community college studies of institutional level variables, Calcagno et al. (2008), for example, found that Full-Time Equivalent student enrollment in community colleges was negatively associated with associate degree and transfer outcomes; however, unlike some other studies (e.g., Freeman, 2007), degree of urbanicity was not statistically significantly related to degree completion or transfer. Similarly, Lynch (2007) found that institutional size was negatively correlated with successful community college student outcomes, though transfer was not considered.

2.2.2: Student Compositional Characteristics

A few studies have demonstrated the associations between student compositional characteristics and student outcomes. For example, Wassmer et al. (2004) in a study of California Community Colleges found that greater institutional percentages of Asian, Male, and younger (under 25 years of age) students were positively associated with institutional transfer rates to four-year institutions. Similarly, Calcagno et al. (2008) found that, after controlling for several individual and institutional level variables, the proportion of full-time equivalent minority students, was negatively associated with degree completion and/or transfer to four-year colleges. Moreover, Lynch (2007) demonstrated that a greater percentage of part-time students was negatively associated with graduation rates.

Other studies have examined the effects of institutional level graduation rates on students' individual probabilities of graduating. For example, Goble et al. (2008) found that community college institutional graduation rates were positively associated with increases in individual student graduation rates, but only for middle achieving students; the relationship did not hold for low and high achieving students. Likewise, there is some evidence that greater overall college transfer rates may also increase the probability of transfer at the student level (LaSota, 2013).

These studies suggest that, like studies of school effects in high school, the student composition of a community college has an effect over and beyond that of the individual student's characteristics. These effects could be in the form of peer effects (Hanushek, Kain, Markman, & Rivkin, 2003) or differing college policies and procedures that are associated with positive outcomes, and vary according to college student compositions (Rumberger & Palardy, 2005). In either case, this is an area for further research.

2.2.3: Community College Faculty

One institutional level variable that has received considerable attention in the literature is the proportion of part-time faculty at community colleges. With the exception of one study conducted in Virginia by Porchea et al. (2010), studies indicate that the proportion of part-time faculty in community colleges is negatively associated with degree and transfer outcomes (Calcagno et al., 2008; Jacoby, 2006; Kevin Eagan & Jaeger, 2009; Lynch, 2007).

Jacoby (2006) found that the percentage of part-time faculty was negatively correlated with community college graduation rates. In addition to the proportion of part-time faculty, Jacoby (2006) also analyzed the association between faculty to student ratios and community college degree completion. Lower faculty to student ratios were associated with lower graduation rates. However, as the proportion of part-time faculty increased, the faculty to student ratio also tended to increase. Interestingly, the increases in faculty to student ratios, while positively associated with degree completion, were unable to undo the negative effects associated with greater proportions of part-time faculty.

Nevertheless, the previous study was conducted at the institutional level, using aggregated college-level data without controlling for student level variables. Porchea et al. (2010), on the other hand, conducted a multilevel analysis, which did control for student level variables. The results from their study indicated that the proportion of part-time faculty was not related to degree completion, but it was statistically significantly negatively associated with transfer.

Some researchers posit that part-time faculty are potentially less available for students outside of class, thus reducing opportunities for student engagement (Jacoby, 2006). Other authors attribute the negative effects of part-time faculty to matters of teacher qualification (i.e., lower educational credentials), or pedagogical ability (Benjamin, 2003). Still others posit that the negative effects of part-time faculty on community college outcomes is due to grade inflation, which has the potential to lower students' potential of passing subsequent courses not taught by part-time faculty. This premise is based on the notion that part-time faculty are more likely to inflate grades in order to receive higher ratings on student evaluations, the results of which play a key role in continued employment opportunities (McArthur, 1999).

It is therefore unclear what the specific mechanism is behind the mostly negative effects of part-time faculty on community college outcomes. This too is an area for further research.

2.2.4: Community College Finance

Some studies have examined the relationships among financial expenditures, tuition costs and various community college student outcome measures. For example, Lynch (2007) found that, at the institutional level of analysis, instructional expenditures per full-time equivalent student were positively associated with graduation rates, while student service expenditures were not. However, when both student level variables and institutional variables were analyzed together, student service expenditures were positively associated with the probability of student graduation, whereas instructional expenditures were no longer statistically significantly related to a student's probability of graduating. Conversely, Calcagno et al. (2008) found that neither instructional nor student service expenditures were related to degree or transfer outcomes. Interestingly, however, academic support expenditures were negatively associated with degree and transfer outcomes.

With respect to tuition, Yang (2005) examined the relationship between two-year and four-year gaps in tuition costs and student transfer to four-year institutions. After controlling for several student and institutional level variables, larger gaps between two and four-year tuition costs were negatively associated with transfer, especially for Black and Hispanic students. Referred to as "sticker shock," it is argued that larger tuition gaps cause students, especially those from less privileged backgrounds, to reassess the cost-benefit of attending a four-year institution.

Similarly, Porchea et al. (2010) found that an increase in community college tuition was associated with a greater likelihood of transferring to a four-year institution. That higher tuition was associated with a greater likelihood of transfer could be related to the above mentioned gap in tuition between two and four-year colleges (Yang, 2005). Alternatively, students who are willing to pay higher tuition fees also may be more committed to their educational goals.

2.3: State Level Variables

While some studies have examined institutional-level variables, few studies have examined the effects of state-level variables on community college transfer. One of the few studies of state-level policies examined the effect of transfer articulation on the probability of transferring to four-year institutions (Anderson et al., 2006). However, the results showed that statewide community college/four-year articulation policies were not related to the conditional probability of transfer.

In addition to transfer articulation policies, Wellman (2002) posited that common statewide course numbering, the use of a common statewide assessment instrument, and governance structures that are organized centrally rather than locally are associated with higher transfer rates to four-year institutions. With respect to common course numbering, LaSota (2013) found that controlling for student, institutional and other state level factors, common course numbering was a statistically significant predictor of transfer, though the effect size was small.

In all, there is very little research that has examined the associations between institutional and state level variables and transfer likelihood. However, surely institutional and state level policies have the potential to affect transfer rates. For example, with respect to remediation, colleges could change their assessment policies to use high school transcript information rather than placement tests. Further, on the same topic, states could change education law to stipulate that colleges must rely more heavily on high school transcript data, etc. In any event, this too is an area for further research.

Unfortunately, as mentioned above, I was unable to conduct a multilevel analysis due to limitations in currently available software.

CHAPTER 3: METHODS

In this dissertation, I used the general statistical technique of structural equation modeling to explore the associations among first-year public community college student demographics, hypothesized transfer subtypes, academic engagement, exposure to remediation, academic performance, and subsequent 4-year transfer likelihood. The measurement model employs both a latent class analysis (LCA) as well as a confirmatory factor analysis (CFA). I utilized the former to identify hypothesized measurement error corrected transfer subtypes (latent classes) and the latter to measure student engagement—a hypothesized continuous latent variable. Before proceeding to the structural equations, I attempted to establish measurement invariance for both the categorical and continuous latent variables across gender, minority status, and first-generation college status.

Finally, after specifying the measurement model and assessing measurement invariance, I examined the structural relationships among the above mentioned latent and observed variables and four-year transfer likelihood. Additionally, I also examined whether transfer subtype moderated any potential relationships between student engagement, remediation, academic performance and 4-year transfer likelihood.

In this chapter, I begin with a discussion of the overall dataset and the particular sample I selected for my analysis. Second, I revisit my conceptual model and discuss the observed variables used to measure the proposed constructs. Third, I briefly discuss the statistical methods used in this study and describe how I assessed the fit of both the measurement and structural models. Finally, throughout this chapter I provide rationale for the methodological decisions I made and discuss their advantages vis-à-vis my research questions.

This study focuses on the associations among student background characteristics, transfer subtypes and experiences in the first year of college (2003-04) and eventual transfer status five years later (2008/09). Adelman (2005a, 2006), for example, has demonstrated that student's initial experiences are strongly associated with subsequent academic outcomes. Therefore, unlike other studies, I do not consider experiences that are most likely to occur beyond the first year (e.g., Associate Degree completion).

3.1: Data and Sample

The sample for this study originates from the 2003/04 Beginning Postsecondary Students Longitudinal Study (BPS: 04/09) conducted by the National Center for Education Statistics (NCES). The BPS: 04/09 includes a sample of nearly 16,700 postsecondary education students who enrolled for the first time in 2003/04 and were followed for six years until 2008/09.

In order to be included in the BPS: 04/09 cohort, students must have been enrolled in 2003/04 at an institution included in the 2004 National Postsecondary Student Aid Study (NPSAS: 04). NPSAS: 04 eligible institutions comprised all colleges and universities located in the United States and Puerto Rico that were eligible to distribute Title IV financial aid funds. In addition to attending an eligible institution, students eligible for inclusion in the NPSAS: 04 also must have been enrolled in an academic program, at least one degree/occupational/vocational applicable credit course or a vocational/occupational program requiring at least 3 months or 300 clock hours (Wine, 2011).

Of the roughly 90,000 students sampled in the NPSAS: 04, approximately 19,000 were categorized as first-time beginning postsecondary students in 2003/04. Accordingly, the base sample for the BPS 04/09 cohort consisted of these 19,000 NPSAS: 04 students who were identified as first-time beginners. However, in order to be considered a BPS:

04/09 study respondent, a sample member's requisite data had to be available either through student interviews or institutional reports. Removing students without the requisite data and those who were deceased at the end of the study resulted in a final sample of roughly 16,700 first-time beginning college students.

3.1.1: Sub-Sample Selection of Two-Year Public Community College Students

Because the goal of this dissertation is to test a structural model of two-year public community college transfer to four-year institutions, I further limited the dataset to include only students who began their postsecondary journey at a community college. However, unlike many transfer studies, I do not limit the universe of potential transfers to include only those students who indicate transfer as their educational goal nor do I limit my sample to students enrolled in a threshold number of units, etc.

First, using the Electronic Cookbook supplied by NCES for use with the restricted BPS:04/09 dataset, I generated the necessary SPSS syntax to produce the initial SPSS data files, variable labels and value labels. After joining together several SPSS data files, the initial dataset consisted of more than 1700 variables and roughly 16,700 cases.

Second, I limited the dataset to include only students whose first institution was a public two-year community college. This was accomplished by selecting cases where FSECTOR9 was equal to category "2." This variable and the distribution of its unweighted categories are shown in Table 1.

Table 1. First Institution Type 2003/04 (BPS:04/09: FSECTOR9).

	Description	Frequency	Percent
1	Public less-than-2-year	425	2.5%
2	Public 2-year	5,549	33.3%
3	Public 4-year nondoctorate-granting	1,595	9.6%
4	Public 4-year doctorate-granting	3,048	18.3%
5	Private not-for-profit less than 4-year	435	2.6%
6	Private not-for-profit 4-yr nondoctorate-granting	2,188	13.1%
7	Private not-for-profit 4-year doctorate-granting	1,496	9.0%
8	Private for-profit less-than-2-year	1,057	6.3%
9	Private for profit 2-years or more	891	5.3%
	Total	16,684	100.0%

Third, after limiting the cases to the 5,549 students whose first institution was a public two year community college, I further limited the sample to include only those students whose first collected institution was also the NPSAS: 04 sampled institution. Because some variables refer to students' experiences at their first institution and others to their NPSAS: 04 institution, including only those students whose first year institution is their NPSAS institution reduces statistical complications related to cross classifications and provides greater internal validity for substantive inferences regarding any potential institutional effects on 4-year transfer likelihood.

Finally, as I will address in more detail, the BPS: 04/09 employed a complex multi-stage sampling design in which institutions were selected first, followed by students within the selected primary sampling units (PSU). For this reason, and to account for unequal probabilities of selection as well as non-response bias, NCES applies a response adjusted, calibrated weight to each case (Folsom & Singh, 2000). In some cases, particular sample members' responses do not add to the sample's overall generalizability to the target population. In these instances, the sample weight is set to zero. Therefore, in addition to the two above mentioned criteria, I also excluded any cases where the sample weight (WTB000) was zero.

After limiting the dataset as described, the remaining sample for this study consisted of 5,081 first-time beginning postsecondary students attending 302 public two-year community colleges across the United States and Puerto Rico.

3.1.2 Issues Related to Complex Survey Design

The BPS: 04/09 employed a complex multi-stage sampling design in which a stratified random sample of institutions was selected first, followed by students within selected institutions. In contrast to a simple random sample (SRS), NCES researchers first stratified the primary sampling units (PSU) across several relevant institutional characteristics (e.g., institution type/control, enrollment, geographic location, etc.) gleaned from the Integrated Postsecondary Data System (IPEDS) Institutional Characteristics and Enrollment files. After stratifying the primary sampling units, researchers randomly selected institutions within each strata. However, some types of institutions were oversampled in order to increase the precision of estimates for particular subgroups, (e.g., community colleges). Finally, students within selected institutions were selected at fixed-type sampling rates to equalize the probability of selection across student types within institution type (Wine, 2011).

Clearly, the BPS:04/09 sampling differs from a simple random sample (SRS). Unlike a simple random sample, the BPS:04/09 sample consists of randomly selected students within a random selection of clusters within identified strata, some of which were oversampled. Because students were sampled with unequal probabilities of selection, using stratification and cluster sampling, researcher’s must account for these design effects in order to make valid inferences from the BPS:04/09 sample to the target population (Fowler, 2014).

Compared to a simple random sample, stratification generally results in smaller standard error estimates, whereas clustering has the opposite effect (Fowler, 2014). Consequently, failure to account for stratification may increase the risk of Type II errors, whereas failure to account for clustering may increase the risk of Type I errors.

One common measure of the degree to which sampling error in complex samples differs from the sampling error expected from simple random samples is provided by the Design Effect (Kish, 1965; Kish & Frankel, 1974). The Design Effect, or *DEFF*, is equivalent to the ratio of the corrected variance of a complex sample to the variance one would receive if the sample had been obtained through simple random sampling. In other words, the Design Effect is the factor by which the variance of an estimator is either under or overestimated compared to the estimation of variance under simple random sampling.

Ganninger (2010) provides a general formula for calculating the Design Effect ($Deff$) that accounts for both unequal probabilities of selection ($Deff_p$) and clustering ($Deff_c$):

$$Deff = Deff_p \cdot Deff_c \tag{1}$$

Where:

$$Deff_p = n \cdot \frac{\sum_{i=1}^{n} w_i^2}{\left(\sum_{i=1}^{n} w_i^2\right)^2} \tag{2}$$

$$Deff_c = 1 + (\bar{b} - 1) \cdot \rho \tag{3}$$

w_i = the design weight for the ith case
n = number of sampling units selected
$\bar{b}$ = the average cluster size
ρ = the intraclass correlation

The intraclass correlation (ICC or ρ) describes the proportion of total variance that exists between clusters. It is also, therefore, a measure of the degree of homogeneity within clusters. For example, if ρ = .10 for a variable of interest in a complex sample, this indicates that 10 percent of the total variance exists between clusters, and, alternatively, the expected correlation between two randomly selected units on this variable in a given cluster would be .10 (Heck & Thomas, 2015; Hox & Roberts, 2011).

Raudenbush and Bryk (2002) present the intraclass correlation for a linear model as follows:

$$\rho = \frac{\tau_{oo}}{\left(\sigma^2 + \tau_{oo}\right)} \tag{4}$$

Where:

τ_{oo} = Variance between clusters

σ^2 = Variance within clusters

For the purposes of this study, I use a logistic model to describe the probability of transfer – a dichotomous variable. Following Vermunt (2003), the intraclass correlation for a logistic model can be expressed as follows:

$$\rho = \frac{\tau_{oo}}{\left(\frac{\pi^2}{3} + \tau_{oo}\right)} \tag{5}$$

Where:

τ_{oo} = Variance between clusters

$\frac{\pi^2}{3}$ = Variance within clusters or the level 1 variance of the logistic distribution (≈3.29)

It is evident from equation 3 that after accounting for the unequal weighting effect ($Deff_p$), the effect of clustering ($Deff_c$) depends on the magnitude of the intraclass correlation and the sample size within each cluster, where greater values of the intraclass correlation and larger cluster sizes lead to greater design effects.

Using the SPSS 22 Complex Sample module, which accounts for stratification, weighting, and clustering, the design effect for my dichotomous transfer variable was 2.62. In other words, if I failed to account for the complex sampling design of the BPS:04/09 and assumed that the sample was instead a simple random sample, I would underestimate standard errors by roughly 2.6 times thus significantly increasing the probability of committing a Type I error.

There are two appropriate options for dealing with clustering in complex multistage samples like the BPS: 04/09. The first approach is to conduct a single level analysis where standard errors and statistical tests are adjusted to account for the design effect (Satorra & Muthen, 1995). The second option is to conduct a multilevel analysis wherein a model at both the within and between levels is specified. In both cases, the researcher must also account for stratification and unequal weighting at the within and, if modeled, the between levels (Asparouhov, 2006; Heck & Thomas, 2015; Stapleton, 2008).

Raudenbush & Byrk (2002) cite three major advantages associated with multilevel model-based approaches to analyzing clustered data. First, multilevel modeling can result in improved estimation of individual effects by borrowing information from higher level units. Second, multilevel modeling allows the researcher to examine how variables at one level affect variables and relationships at another level. Third, Raudenbush & Byrk (2002) note that an additional strength associated with multilevel modelling is the ability to partition variance-covariance components across levels, thus allowing the researcher to disentangle, for example, what proportions of variance in a given outcome exist within and between clusters.

Although there are clear statistical and substantive reasons for choosing a model-based approach to the study of BPS: 04/09 data, at the time of this dissertation, software limitations (Mplus v. 7.3) precluded a multilevel analysis. When I posed my particular question to the Mplus discussion forum regarding a two-level mixture model using the three step process, T. Asparouhov responded as follows:

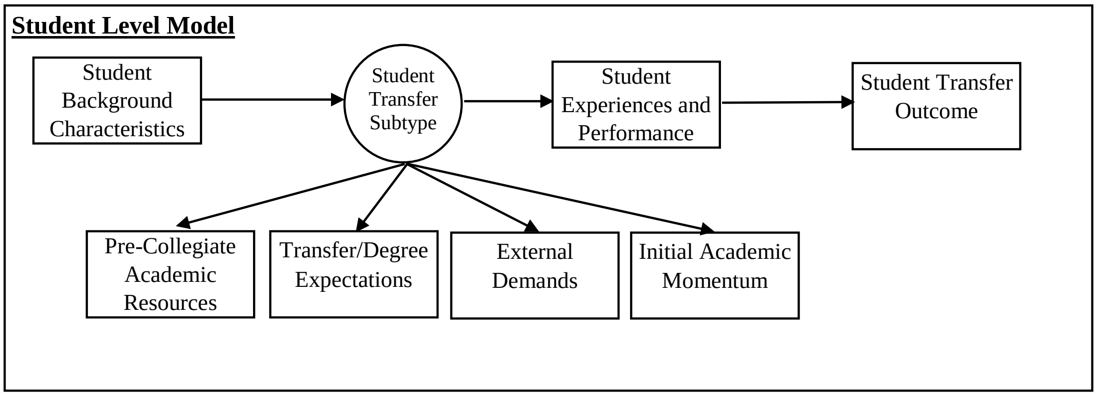
> I can recommend only TYPE=COMPLEX MIXTURE. The 3 step methodology has not been developed and used yet for TYPE=TWOLEVEL MIXTURE (Asparouhov, 2014).

Therefore, to account for the complex sampling design of the BPS 04:09, I employ the COMPLEX command, in conjunction with the SUBPOPULATION, STRATIFICATION and CLUSTER commands to identify the variables that represent the PSU, Stratum, and design weight.

3.2: Conceptual Model

Figure 2 represents the basic conceptual framework that guides the models that I test in this dissertation.

Figure 2. *Conceptual Model – Student Level Only.*



To begin, the model posits a population of community college students who are heterogeneous with respect to their status on several literature supported dimensions related to community college transfer. This heterogeneity, it is argued, can be modeled using a latent class analysis. The model further hypothesizes that the resulting measurement error corrected latent classes will consist of an unspecified, but small number of meaningful transfer subtypes, wherein students' response patterns vis-à-vis the indicators that represent the dimensions of Pre-collegiate Academic Resources, Transfer/Degree Expectations, External Demands, and Initial Academic Momentum will be similar within and different across classes. Further, the model also assumes that student demographic variables affect latent class membership.

The model further posits that latent class membership predicts levels of student engagement, participation in remediation, first-term GPA, as well as transfer status. Finally, the model hypothesizes that the associations between remediation, student engagement, first-term GPA and transfer vary by latent class, i.e. latent class membership moderates the relationships between student experiences/academic performance and transfer likelihood.

Most studies model transfer as a process in which student background variables affect pre-collegiate academic achievement as well as initial educational aspirations to transfer, which in turn affect students' academic momentum, need for remediation, level of engagement and ultimately, community college academic performance and credentials. At the same time, external demands and/or support affect students' academic momentum, engagement, and community college academic achievement. Finally, directly and indirectly, these measured and latent variables influence a student's likelihood of transferring to a four-year institution.

Most importantly, if this model is successful in, first, identifying substantively useful subtypes of beginning community college students and, second, the relationships between malleable student experiences and transfer vary by latent class, then the results could be used as an upfront assessment and advising tool to provide targeted advice/interventions specific to students who belong to each latent class. Therefore, as mentioned, I do not consider experiences that are most likely to occur beyond the first year (e.g., Associate Degree completion).

Finally, as mentioned above, although displayed in my initial conceptual model, I was unable to conduct a multilevel analysis using the three-step procedure. Consequently, I only test the student level model displayed in Figure 2.

3.3: Selection of Variables

The ultimate goal of this dissertation is to build and test a structural model of community college student transfer to four-year institutions. Therefore, the first step, after limiting the sample as delineated in section 3.1.1, was to identify students who did and did not transfer to 4-year institutions within the six year time period. For the purposes of this study, I used the variable CCSTAT6Y to create a dichotomous variable of transfer status. Specifically, I recoded CCSTAT6Y into a dichotomous variable named TRANSFER where any case equal to category 8, "Transferred to 4-year without AA" or 9, "Transferred to 4-

year with AA" was coded as 1, "Transferred to a 4-year institution" otherwise my new variable, TRANSFER was coded as 0 "Did not Transfer to a 4-year institution." The TRANSFER variable included 1,400 (unweighted) students who had transferred to a 4-year institution within six years and 3,680 who had not. Table 2 displays the categories of variable CCSTAT6Y and the weighted percent of cases falling in each category. Table 3 provides the same information for my newly recoded dichotomous variable, TRANSFER.

Table 2. CCSTAT6Y: Six-Year Retention and attainment 2009.

Description	Percent
First institution is not public 2-year*	0.00%
Not enrolled, no degree	37.6%
Not enrolled, attained AA	6.4%
Not enrolled, attained certificate	4.2%
Enrolled, no degree	9.0%
Enrolled, attained AA	2.7%
Enrolled, attained certificate	0.7%
Transferred to 2-year or less	15.2%
Transferred to 4-year without AA	18.0%
Transferred to 4-year with AA	6.2%
Total	100.0%

* Only public 2-year colleges were included in the sample

Table 3. TRANSFER: Transfer Status after 6 years (recoded).

	Description	Percent
0	Did not Transfer to 4-year insitution	75.9%
1	Transferred to 4-year institution	24.1%
	Total	100.0%

In addition to the dichotomous outcome variable, TRANSFER, I selected literature and dataset supported variables that corresponded to the general constructs proposed in my conceptual model. From least to conceivably most malleable, the observed variables I selected can be characterized as belonging to one or more of the following dimensions: (i) Student Background Characteristics, (ii) Academic Resources, (iii) Degree Expectations/Transfer intentions, (iv) External Demands, (v) Academic Momentum, and (vi) Student Experiences/Academic Performance.

With respect to their function within my conceptual model, student background characteristics serve as covariates, academic resources degree expectations/transfer intentions, external demands, and academic momentum define the latent classes, while Student Experiences/Academic Performance represent the potentially malleable variables that affect transfer and are associated with latent classes.

Unlike other national postsecondary databases, the BPS:04/09 samples all first-time beginning postsecondary students regardless of age at entry or date of high school graduation. That all first-time beginning postsecondary students are included in the BPS:04/09 is important for any study of community college outcomes, given, for example, that nearly 48% (weighted) of community college beginners in my selected sample delayed postsecondary entry by at least one year (BPS:04/09).

Although the BPS:04/09 is generally well suited to the study of community college student outcomes, it is somewhat limited in its coverage of high school academic performance measures. First, one of the most important markers of high school academic performance—high school GPA—is available only for students who took the SAT or ACT. Second, where high school academic performance information is available, e.g., highest math course completed, etc., it is available only for students under the age of 24. Consequently, high school GPA is structurally missing for more than 35% of the overall weighted sample.

Given that the BPS: 04/09 fails to collect potentially important pre-college data (e.g., Entrance Exam data, high school course taking, high school GPA, etc.) for students who are 24 years of age and older, my study design is therefore further limited to include only students under the age of 24. It is unclear and unpublicized as to why the BPS: 04/09 fails to collect the same information for students 24 years of age and older as it does for those under 24; one potential explanation could be related to financial independence, which all students 24 and over are considered to be. Consequently, the final effective sample size for this study consists of 3,940 students attending 292 public community colleges. Descriptive statistics (weighted) for the final sample are displayed in Table 4 below.

Table 4. Descriptive Statistics of Final Sample.

		% of Total sample	% Transferred
Student Background Characteristics	**Gender**		
	Male	46.6%	29.5%
	Female	53.4%	30.5%
	First Generation Status		
	First Generation Student	67.2%	25.6%
	Not First Generation Student	32.8%	39.0%
	Race/Ethnicity		
	Hispanic, Black, Other	34.0%	26.1%
	White or Asian	66.0%	32.0%
Academic Resources	**High School Academic Achievement**		
	Low	54.3%	24.9%
	Medium	23.1%	30.5%
	High	22.6%	41.6%
	Took College Admission Exams		
	Did not Take ACT/ACT	31.4%	18.3%
	Took ACT/SAT	68.6%	35.3%
Degree Expectations/ Transfer Intentions	**Transfer Plans**		
	Did not plan to transfer to 4-year	34.7%	14.4%
	Planned to transfer to 4-year	65.3%	38.2%
	Degree Expectations		
	Below Bachelor's	13.1%	10.8%
	Bachelor's	38.4%	27.1%
	Above Bachelor's Degree	48.5%	37.4%
Academic Momentum	**Enrollment Intensity**		
	Part-Time Only	30.7%	17.3%
	Full-Time/Mixed	69.3%	35.6%
	Delayed Enrollment		
	Delayed	32.8%	20.5%
	Did not Delay	65.8%	34.5%

Table 4. Descriptive Statistics of Final Sample (continued).

		% of Total Sample	% Transferred
External Demands	**Employment**		
	Work Full-time	24.7%	21.8%
	Work Part-Time	53.1%	33.8%
	Not Employed	22.2%	30.1%
	Financial Independence		
	Independent with Dependents	8.3%	15.2%
	Independent without Dependents	4.4%	21.8%
	Dependent	87.3%	31.8%
Student Experiences	**Remediation**		
	Took Remedial	32.5%	23.5%
	Did not take Remedial Course	67.5%	33.1%
	Engagement		
	Meet with Faculty Informally		
	Never	69.4%	28.8%
	Sometimes	25.6%	31.2%
	Often	5.1%	39.7%
	Talk with Faculty Outside of Class -Academic		
	Never	32.8%	24.5%
	Sometimes	55.5%	31.0%
	Often	11.7%	40.9%
	Meet with Advisor		
	Never	41.2%	23.5%
	Sometimes	46.9%	32.4%
	Often	11.9%	43.0%
	Participated in Study Groups		
	Never	61.5%	26.6%
	Sometimes	32.2%	34.0%
	Often	6.4%	42.0%
Academic Performance	**First-year College GPA***	2.76	3.01

**Represents mean first-year GPA*

3.3.1: Covariates - Student Background Variables

While the literature points to several demographic variables associated with community college transfer, due to limitations in the BPS: 04/09, only three are included: Gender, Minority Status, and First-Generation College Status. Unfortunately, the BPS:04/09 does not include a composite measure of Socioeconomic Status (SES), but it does include the highest level of education completed by either parent—an important component of traditional SES composites (Sirin, 2005). While other components of SES are available, their collection is inconsistent, e.g., income represents parental income for dependent students and student income for independent students. The original and recoded student background variables are described in Table 5.

Table 5. Student Background Variables.

Original BPS:04/09 Variables		Renamed and Recoded Variables used in this study			
Variable	**Description**	**Variable**	**Description**	**Recoded**	**Value Labels**
GENDER	Indicates the respondent's gender.	*GENDER*	*Same as BPS:04/09 original variable description*	*Yes*	*0 = Male* *1= Female*
RACE	Race/ethnicity	*MINORITY*	*Indicates underrepresented minority status.*	*Yes*	*0 = Not White/Asian* *1 = White/Asian*
TRIO	TRIO program eligibility criteria 2003-04	*FIRST_GEN*	*Indicates whether either parent completed a Bachelor's Degree or Higher*	*Yes*	*0 = First Generation (neither parent completed Bachelor's Degree or higher)* *1 = Not First Generation (at least one parent completed a Bachelor's Degree or higher)*

3.3.2: Latent Class Indicators – Academic Resources

As cited in my literature review, the academic resources students amass in high school are correlated with their eventual likelihood of 4 year transfer. To measure academic resources, I first create a composite variable, *HSACH*, to indicate the rigor of the student's high school curriculum. An ordinal variable, *HSACH* provides three levels of curriculum rigor based on the number of years of study in various subjects and the highest level of math class completed. Second, I include a dichotomous variable, TEST_TAKE, indicating whether the student took either the SAT or ACT college admission exams.

Unfortunately, high school GPA is structurally missing for all students who did not take the SAT or ACT, and, therefore, is not included in my analysis. Further, as mentioned, high school academic information in the BPS:04/09 is limited in general and unavailable for any student 24 years of age or older. The variables representing academic resources are described in Table 6.

Table 6. Academic Resources.

Original BPS:04/09 Variables		Renamed and Recoded Variables used in this study			
Variable	**Description**	**Variable**	**Description**	**Recoded**	**Value Labels**
ACG1	Academic Competitiveness Grants (ACG) curriculum eligibility 2003-04	*HSACH*	*A composite of variables ACG1 and HCMATH, indicates the rigor of the respondent's high school course-taking. Students who met the ACG curriculum eligibility requirements completed 4 years of English, 3 years of Math, Science, and Social Science, as well as 1 year of Foreign Language study*	*Yes*	*0 = Did not meet ACG Curriculum requirements 1 = Met ACG Curriculum requirements and highest Math course was Algebra II 2 = Met ACG curriculum requirement and highest Math course was above Algebra II*
HCMATH	Highest level of high school mathematics				
TETOOK	SAT or ACT exams taken	*TEST_TAKE*	*Indicates whether the respondent took the SAT or ACT college entrance exams*	*Yes*	*0 = Did not take the SAT or ACT 1 = Took the SAT or ACT*

3.3.3: Latent Class Indicators – Transfer Intentions

Because community colleges have multiple missions and therefore serve students pursuing disparate paths, it is difficult to ascertain which students actually intend to transfer to 4-year institutions. As indicated, transfer intention is, for obvious reasons, highly correlated with transfer likelihood. The first variable, *TRANSPLN,* is a dichotomous variable indicating the student's self-reported plans to transfer to a 4-year institution. Second, I create an ordinal variable, *DEGASP,* that represents the student's self-reported, highest level of education ever expected.

As an aside, although the variable *TEST_TAKE* is employed as an indicator of academic resources, taking a college admission test might also indicate an initial intention to attend a 4-year institution given that college admissions tests are irrelevant to community college attendance.

The variables representing transfer intention/degree expectations are described in Table 7 below:

Table 7. Transfer Intention/Degree Expectations.

Original BPS:04/09 Variables		Renamed and Recoded Variables used in this study			
Variable	**Description**	**Variable**	**Description**	**Recoded**	**Value Labels**
HIGHLVEX	Highest degree ever expected 2003-04	*DEGASP*	*Same as BPS:04/09 original variable description*	*Yes*	*1 = Below Bachelor's Degree (i.e., Associate degree, Certificate or no award)* *2 = Bachelor's Degree* *3 = Above Bachelor's Degree (e.g., Masters,Doctoral, etc.)*
TRPLNY1	Transfer plans 2003-04	*TRANSPLN*	*Same as BPS:04/09 original variable description*	*No*	*0 = Did not plan to transfer to 4-year institution* *1 = Planned to transfer to 4-year institution*

3.3.4: Latent Class Indicators – External Demands

External demands tend to reduce students' ability to engage fully with college and are therefore associated with lower probabilities of 4-year transfer. To measure the degree of environmental pull, first I create an ordinal variable, *FIN_IND*, which represents whether the student is financially dependent, independent, or independent with dependents. Dependent students are unmarried, without children and financially dependent on their parents/guardians. Independent students may be married or not, do not have children, but are financially independent. Finally, independent students with dependents may be married or not, have dependent children and are financially independent.

Second, I create another ordinal variable, *WORK*, that indicates whether the student is not working, working part time (less than 35 hours/week), or working full-time (35+ hours/week). Table 8 below describes the aforementioned variables.

Table 8. External Demands.

Original BPS:04/09 Variables		Renamed and Recoded Variables used in this study			
Variable	**Description**	**Variable**	**Description**	**Recoded**	**Value Labels**
DEPEND5A	Dependency and marital status (separated=married) 2003-04	*FIN_IND*	*Indicates respondent's dependency status and whether the respondent has dependents*	*Yes*	*1 = Independent with Dependents* *2 = Independent with no Dependents* *3= Dependent (no Dependents)*
JOBHOUR	Job while enrolled 2004: Hours worked per week (excl work study)	*WORK*	*Same as BPS:04/09 original variable description*	*Yes*	*1 = Employed Full-Time (35+ hours/week)* *2 = Employed Part-time (Less than 35 hours per week)* *3 = Not Employed*

3.3.5: Latent Class Indicators – Academic Momentum

Several studies have demonstrated the significant correlations between, what Adelman (2006) refers to as, academic momentum and several positive educational outcomes. The first indicator of academic momentum I include is a dichotomous variable, *DELAY*, indicating whether or not a student delayed community college enrollment for at least one year after high school graduation. Students who did not graduate high school or were 24 years of age or older were assigned to the “Delayed” category. Students who both enrolled at a community college immediately after high school graduation and were under the age of 24 were assigned to the “Did not Delay” category.

The second variable I include to measure academic momentum is a dichotomous variable, *FULL_TIME*, which indicates whether the student was enrolled full-time or less than full-time during the months enrolled in the primary year. Table 9 describes the variables I chose to measure academic momentum.

Table 9. Academic Momentum.

Original BPS:04/09 Variables		Renamed and Recoded Variables used in this study			
Variable	**Description**	**Variable**	**Description**	**Recoded**	**Value Labels**
DELAYENR	Delayed enrollment into PSE: Number of years 2003-04	*DELAY*	*Indicates respondent's high school graduation status and whether the respondent delayed enrollment into postsecondary education.*	*Yes*	*0 = Delayed entry into Postsecondary Education or did not receive a high school diploma or 24+ years of age* *1 = Did not Delay entry into Postsecondary Education after receiving high school diploma (under 24 years of age)*
HSDEG	Indicates whether the respondent has graduated from high school and the type of high school diploma received.				
FALLHSFT	This variable categorizes beginners who were also recent high school graduates, based on degree plans and fall 2003 full time enrollment status.				
AGE	Age first year enrolled				
ENINPT1	Indicates the pattern of enrollment intensity for the months the respondent was enrolled during the 2003-2004 academic year.	*FULL_TIME*	*Same as BPS:04/09 original variable description*	*Yes*	*0 = Enrolled less than Full-time* *1 = Enrolled Full-time*

3.3.6: Student Experiences – Academic Engagement

The literature is somewhat mixed with respect to the role academic engagement plays in community college outcomes, particularly among studies conducted using the BPS:04/09 (Greene, 2005; Roman, Taylor, & Hahs-Vaughn, 2010). However, in my review of the literature, none of the studies I retrieved employed a latent variable approach to measuring student engagement. Consequently, it is possible that the true relationship between the observed student engagement indicators and community college transfer was attenuated due to low reliability.

As is well known in the educational and psychometric literature (Mehrens & Lehmann, 1987), the maximum theoretical correlation between two variables is less than or equal to the square root of the product of the reliabilities of each variable:

$$r_{xy} \leq \sqrt{r_{xx}\, r_{yy}} \tag{6}$$

Where:

r_{xy} = correlation between two variables

r_{xx} = reliability of variable x

r_{yy} = reliability of variable y

Accordingly, when unreliable measures are used in a simple linear regression, for example, the observed relationship between the variables is attenuated, thereby reducing statistical power and increasing the risk of committing a Type II error (Kline, 2005). In the case of multiple linear regression, the effect of adding unreliable variables can lead to increased risks of Type I errors for other variables in the model, inaccurate attribution of variance explained, and, again, increased risk for Type II errors with respect to each unreliable measure (Osborne & Waters, 2002).

As a result, I use a latent variable modeling approach—confirmatory factor analysis (CFA)—to account for the presumed measurement error in the indicators of what I call student engagement (Brown, 2014). It is hypothesized that modeling the structural relationship between a latent representation of student engagement and transfer may provide greater statistical power to unmask the true underlying relationship.

To represent academic engagement, I chose the same four manifest indicators that NCES researchers use to create their BPS:04/09 variable, “Academic Integration Index 2004.” This variable represents the average of the responses indicating how often the student: (i) had social contact with faculty (*ENGINF*), (ii) talked with faculty about academic matters outside of class (*ENGOUT*), (iii) met with an academic advisor (*ENGADV*) or participated in study groups (*ENGSTUDY*).

Rather than using the existing NCES derived index of academic integration, I use confirmatory factor analysis to identify the common variance explained by the unobserved latent variable. To be discussed in more detail, I hypothesize that by controlling for the unreliability of the observed indicators, the true relationship between the measurement error corrected latent variable and likelihood of transfer will emerge. Table 10 describes the variables I chose to measure Student Engagement.

Table 10. Student Engagement.

Original BPS:04/09 Variables		Renamed and Recoded Variables used in this study			
Variable	**Description**	**Variable**	**Description**	**Recoded**	**Value Labels**
FREQ04A	Indicates whether or how often the respondent had informal or social contacts with faculty members outside of classrooms and the office during the 2003-2004 academic year.	*ENGINF*	*Same as BPS:04/09 original variable description*	*No*	*0 = Never* *1 = Sometimes* *2 = Often*
FREQ04B	Indicates whether or how often the respondent talked with faculty about academic matters outside of class time (including e-mail) during the 2003-2004 academic year.	*ENGOUT*	*Same as BPS:04/09 original variable description*	*No*	*0 = Never* *1 = Sometimes* *2 = Often*
FREQ04C	Indicates whether or how often the respondent met with an advisor concerning academic plans during the 2003-2004 academic year.	*ENGADV*	*Same as BPS:04/09 original variable description*	*No*	*0 = Never* *1 = Sometimes* *2 = Often*
FREQ04G	Indicates whether or how often the respondent attended study groups outside of the classroom during the 2003-2004 academic year.	*ENGSTUDY*	*Same as BPS:04/09 original variable description*	*No*	*0 = Never* *1 = Sometimes* *2 = Often*

3.3.7: Student Experiences – Remediation

As with student engagement, the literature is mixed with respect to the effect of remediation on community college transfer odds. Increasingly, more recent studies suggest that remediation has deleterious effects on several community college outcomes, including transfer (Bahr, 2008b; Calcagno & Long, 2008; Crisp & Delgado, 2014; Scott-Clayton et al., 2014). However, it is unclear whether the effects of remediation are the same across different subtypes of beginning community college students; one of the reasons I chose to use a latent class analysis is to answer just such a question.

Although the BPS: 04/09 includes separate variables to indicate whether students took remedial courses in different subject areas, I create one dichotomous indicator representing enrollment in at least one remedial course, regardless of the subject. While some research has shown positive effects of remediation in some disciplines (i.e., mathematics) and not in others, because of sample sizes across types of remediation, I create one dichotomous measure of remediation exposure. As displayed in Table 11, my dichotomous variable, *REMED,* is set equal to zero if the student took a remedial course in English, mathematics, reading, or writing during the 2003/04 academic year, and to one if not.

Table 11. Remediation.

Original BPS:04/09 Variables		Renamed and Recoded Variables used in this study			
Variable	**Description**	**Variable**	**Description**	**Recoded**	**Value Labels**
REMEDIA	Indicates whether the respondent took remedial or developmental courses in English during the 2003-2004 academic year.	*REMED*	*Indicates whether the respondent took remedial or developmental courses in English, Mathematics, Reading or Writing during 2003-2004*	*Yes*	*0 = Respondent took at least one remedial or developmental course in English, Mathematics, Reading, or Writing during 2003-2004* *1 = Respondent did not take a remedial or developmental course in English, Mathematics, Reading, or Writing during 2003-2004*
REMEDIB	Indicates whether the respondent took remedial or developmental courses in mathematics during the 2003-2004 academic year.				
REMEDIC	Indicates whether the respondent took remedial or developmental courses in reading during the 2003-2004 academic year.				
REMEDIE	Indicates whether the respondent took remedial or developmental courses in writing during the 2003-2004 academic year.				

3.3.8: Student Academic Performance – First-Year Community College GPA

Academic performance in the first year of college is associated with several subsequent community college outcomes, including 4-yr transfer. To measure academic performance, I use 2003/04 grade point average as reported by the institution, or, if unavailable, the student. NCES standardizes the GPA to a 4.0 scale and then multiplies this value by 100. For the final analyses, I divided this variable by 100 and grand mean centered the value to facilitate interpretability of the odds ratios. This variable is described in table 12.

Table 12. Academic Performance.

Original BPS:04/09 Variables		Renamed and Recoded Variables used in this study			
Variable	**Description**	**Variable**	**Description**	**Recoded**	**Value Labels**
GPA	Indicates the respondent's cumulative Grade Point Average (GPA) for the 2003-2004 academic year.	*CGPA*	*Same as BPS:04/09 original variable description*	*No*	*The GPA was standardized to a 4.00 point scale and was multiplied by 100*

3.4: Latent Class Analysis

The first research question I attempt to answer in this dissertation is whether a latent class analysis can identify useful subtypes of transfer risk from students' statuses on several literature based correlates of transfer. In this section, I first provide a brief introduction to latent class analysis, as well as rationale for why I chose this method to address my research questions. Second, I discuss the parameters and their estimation in a general unconditional latent class model as well as the measurement characteristics of desirable manifest items. Third, I describe the various statistical tests and relative fit indices I used to assess model fit and characterize the quality of classification. Finally, I describe the strategies I used to examine measurement invariance of latent classes across several demographic variables.

3.4.1 Introduction to Latent Class Analysis

To begin, all latent variable models posit an unobserved, underlying latent variable or construct that is measured by observed or manifest indicators or items (Brown, 2014; Collins & Lanza, 2010). Also known as categorical factor analysis, latent class analysis is analogous to traditional factor analysis in that both methods assume an underlying latent variable reflected by manifest indicators (Collins & Lanza, 2010; Lazarsfeld & Henry, 1968; Magidson & Vermunt, 2004; McCutcheon, 1987; Stouffer et al., 1950). However, first, latent class analysis differs from traditional factor analysis with respect to distributional assumptions; the former is multinomially distributed whereas the latter is conceived as continuous and normally distributed. Second, from a conceptual perspective, categorical latent variables typically, though not necessarily, describe qualitative differences between groups of subjects, whereas continuous latent factors identify quantitative differences among subjects along a continuum of the putative construct of interest (Ruscio & Ruscio, 2008).

Specifically, because traditional factor analysis focuses on identifying relations among variables that are assumed to hold across individuals, it is often referred to as a *variable-centered approach*, whereas latent class analysis, with its focus on grouping individuals based on similar response patterns, is frequently referred to as a *person-centered approach* (Bergman, Magnusson, & El Khouri, 2003; Collins & Lanza, 2010; Magnusson, 2003).

Nevertheless, Masyn (2013) argues that, while the two approaches answer somewhat different questions, *variable* and *person-centered approaches* may be used in complementary ways. Indeed, in this dissertation, I first use a *person-centered approach* (LCA) to identify individuals with similar response patterns, and second, employ a *variable-centered approach* to examine both predictors of latent class membership and the effect of latent class membership on distal outcomes.

Finally, as in the case of continuous latent variables, categorical latent variables can be measured by continuous, binary, count, etc. indicators or any combination thereof.

However, the term latent class analysis typically refers to measurement models in which the indicators are categorical, whereas latent profile analysis is the conventional name for categorical factor analysis of continuous indicators (Collins & Lanza, 2010).

3.4.2: Unconditional Latent Class Model

To begin, following the notation of Collins and Lanza (2010), the unconditional latent class model assumes an underlying multinomial latent class variable, L, with c = 1,…,C independent latent classes, which accounts for the associations among j = 1,…,J observed categorical items with $r_j = 1,\ldots, R_j$ response categories and $\boldsymbol{y} = (r_1,\ldots,r_j)\ldots,\boldsymbol{Y}$ possible response vectors. From the $\boldsymbol{Y}$ response patterns, two parameters are estimated: (i) latent class prevalences (γ_c's) and item-response probabilities (ρ_j's).

Latent class prevalences represent the estimated probability of membership in latent class c, Pr(L = c) or the estimated proportion of cases in latent class c. Because latent classes are mutually exclusive and comprehensive, $\sum_{c=1}^{C}\gamma_c = 1$, which implies that individuals are assigned to one and only one latent class. Interrelated with latent class prevalences, item response probabilities, $\rho_j, r_j \mid c$ indicate the probability of responding in a specific category, r_j of a given item j, conditional on membership in latent class c. As in the case of latent class prevalences, these estimated, conditional probabilities sum to one: $\sum_{r_j=1}^{R_j}\rho_j, r_j \mid c = 1$ (Collins & Lanza, 2010).

Again borrowing from Collins and Lanza (2010), a general unconditional latent class measurement model can be expressed as follows:

$$P(Y=y)=\sum_{c=1}^{C}\gamma_c\prod_{j=1}^{J}\prod_{r_j=1}^{R_j}\rho_{j,r_j|c}^{I(y_j=r_j)} \tag{7}$$

All the terms in equation 7 are as described above, with the exception of $I(y_j = r_j)$, which is an indicator function that equals 1 if an item in a given response vector, y_j, is equal to a specific response r_j, and 0 if not. Equation 7 shows that the observed responses to the j manifest variables are related to the latent class variable L through a function of both the estimated latent class prevelances (γ_c's) and the conditional item response probabilities (ρ_j's).

In order to use equation 7, the researcher must assume, like in traditional factor analysis, that, conditional on the latent variable, the manifest items are locally independent. That is to say, within a given latent class, the observed items are statistically independent. If this assumption is not met, equation 7 requires conditioning on not only the latent class, but also on each item. While methods have been developed and used to estimate latent class models where local independence fails to hold, these models are much more complicated and used rather infrequently (Collins & Lanza, 2010; Magidson & Vermunt, 2004; Masyn, 2013). To assess the degree of local independence, I examined the statistical significance of the standardized bivariate residuals between each item pair (Agresti, 2013).

3.4.3: Homogeneity and Latent Class Separation

The concepts of homogeneity and latent class separation provide two interrelated criteria by which the researcher can judge the quality of the observed indictors. Analogous to the traditional factor analysis terms of *saturation* and *simple structure*, respectively, homogeneity refers to the strength of the relationship between the indicator and the latent class (akin to factor loadings), whereas latent class separation implies that estimated conditional item response probabilities differ across latent classes (akin to indicators loading on only one factor) For binary items, conditional model estimated item response probabilities close to 0 or 1 indicate a high degree of homogeneity, while a high degree of latent class separation occurs when item response probabilities vary significantly across at least two classes. (Collins & Lanza, 2010; Masyn, 2013; Thurstone, 1954).

Although a high degree of latent class separation implies a high degree of homogeneity, a high degree of homogeneity does not always translate into a high degree of latent class separation. For example, if the estimated conditional item response probability of endorsing a binary item were .9 across all latent classes, such an item would possess a high degree of homogeneity, but demonstrate a low degree of latent class separation.

In practice, neither perfect homogeneity nor perfect latent class separation will exist. However, with respect to assessing the degree of homogeneity, Masyn (2013) suggests that estimated conditional item response probabilities (for binary items) of $>.70$ or $<.30$ are indicative of relatively high homogeneity. In the case of latent class separation, Masyn (2013) recommends examining the ratio of the odds of endorsing an item in a given latent class to the odds of endorsing the same item in a different latent class; high latent class separation is indicated by $O\hat{R} > 5$ or $O\hat{R} < .2$.

Accordingly, I assessed the performance of several candidate indicators by examining their conditional item response probabilities within classes (homogeneity) and the degree to which they varied across at least two classes (latent class separation). I preferred indicators with conditional item response probabilities consistently near $1/r_j$, where r_j represents the number of categories of item *j*. Moreover, I also preferred indicators with $\hat{OR} > 5$ or $\hat{OR} < .2$ when comparing conditional item response probabilities across at least two classes.

3.4.4: Power Considerations

To begin, Finch and Bronk (2011) suggest that researchers aspire to obtain sample sizes of at least 500 when conducting a latent class analysis. However, while large sample sizes generally lead to increased power to retrieve the true population parameters, Wurpts and Geiser (2014) demonstrate via simulation study that performance of latent class analysis is dependent on not only sample size, but also the number and quality (homogeneity) of indicators selected, as well as whether covariates are included in the model. In general, based on the results of the simulation study, using higher sample sizes, including more indicators or increasing the quality of the chosen indicators, and including covariates with moderate to high associations with the latent variable all resulted in lower mean biases in estimated latent prevalences and conditional item response probabilities.

Moreover, Wurpts and Geiser (2014) show that the negative effects of small sample sizes can be ameliorated to some degree by the inclusion of more or higher quality indicators or preferably both. Interestingly, despite the theoretically important concept of homogeneity, their results suggest that adding more indicators, regardless of quality, decreased parameter bias. As a result, Wurpts and Geiser (2014) caution against the use of fewer than five indicators, and do not discourage researchers from adding as many theoretically justified indicators as available.

With respect to my analysis, the sample size is 3,900, significantly exceeding the minimum sample size recommendations cited above. Moreover, based on the substantive literature and the measurement qualities of the indicators, I selected eight indicators to measure the latent class model. Therefore, the minimum recommended sample size and number of indicators is exceeded, thus providing greater power and decreased parameter bias.

3.4.5: Model Estimation

The estimation of latent class models involves estimating both latent class prevalences (γ_c's) and conditional item response probabilities (ρ_j's). Because these unknown parameters do not have a closed form solution, most software programs employ an iterative approach to finding parameter estimates that maximize the likelihood of the observed sample data. However, given that the likelihood function is a product of small values between 0 and 1, and due to the simplification of subsequent calculations (i.e., $\ln xy = \ln x + \ln y$, and $\ln x^a = a \ln x$), the likelihood function is transformed to a logarithmic scale.

Although interest in Bayesian estimation has increased (Asparouhov & Muthén, 2011; Chung & Anthony, 2013; Pan-ngum et al., 2013), most software programs employ a variant of the Dempster, Laird, and Rubin (1977) expectation-maximization algorithm to find maximum likelihood estimates of latent class parameters that maximize the likelihood function. Each iteration consists of an expectation and maximization step. During the E-step, the expected values of parameters are estimated based on the current parameters and the sample data. Next, during the M-step, new parameter estimates are calculated using the current parameters and the observed data such that the maximum likelihood function is further maximized (Masyn, 2013).

To guide the EM algorithm, the researcher must specify both how many iterations to allow, and more importantly, the convergence criterion—the point at which differences in parameter estimates between successive iterations become trivial. Collins and Lanza (2010) suggest that when the maximum absolute difference between any parameter estimate between successive iterations is ≤ .000001, the estimates are considered sufficiently close to their theoretical maximum likelihood estimates.

Because it is impossible to prove that a unique global maximum of the likelihood function exists, the researcher can never be assured that the arrived upon solution represents a global maximum rather than a local maximum. Given the possibility that several local maxima exist, one strategy for increasing confidence that the arrived upon maximum likelihood solution is not a local maximum is by specifying many different starting values for the search algorithm. If the same maximum of the likelihood function is replicated across a minimum of 50 to100 (or more) sets of random starting values, the researcher has more confidence that the solution is indeed the maximum likelihood solution (Collins & Lanza, 2010; Masyn, 2013).

All my analyses related to the measurement and structural model were conducted using Mplus version 7.3. For all analyses involving latent class analyses, I selected ANALYSIS TYPE = COMPLEX MIXTURE, which by default selects the MLR estimator, which employs the EM algorithm described above. The MLR estimator is a maximum likelihood estimator that produces standard errors robust to both non-normality and non-independence of observations and a χ^2 statistic that is equivalent to the Yuan-Bentler T2* test statistic (Brown, 2014; Muthén & Muthén, (1998-2012); Yuan & Bentler, 2000).

To increase confidence that the global maximum of the likelihood function had been found, in my final latent class analyses, I specified STARTS = 10000 500 and STITERATIONS = 250, which instructs Mplus, first, to generate 10,000 random starting values and conduct 250 iterations of the maximization for each of the 10,000 starting values.

Second, Mplus takes the parameter estimates from the 500 best likelihood values obtained in the first step and uses those for starting values in the final optimization. The convergence criterion is set at .000001 by default.

3.4.6: Missing data

Rubin (1976) categorizes missing data into three subtypes, two of which represent *ignorable missingness* and the last *non-ignorable missingness*. Data that are missing completely at random (MCAR) or, less restrictively, missing at random (MAR) are considered *ignorable missingness*, while data missing not at random (MNAR) are considered *non-ignorable missingness*. Data are considered MCAR when the missing values are neither related to other observed variables nor to the value of the missing variable itself. Similarly, data are considered MAR if the missing values *are* related to other observed variables, but not to the value of the missing variable itself. Finally, data are considered MNAR if the missing values are related to the value of the missing variable (Enders, 2010; Little & Rubin, 2014).

If the missing data are MCAR or MAR, then either Full-Information Maximum Likelihood (FIML) approaches, including those using the above mentioned EM algorithm, or Multiple Imputation can be used to analyze both the complete and incomplete cases. Both methods produce unbiased and consistent estimates in the face of missing data. Although, because FIML approaches do not require the creation of several datasets as in the case of Multiple Imputation, and because FIML requires no further specification by users, FIML has become the de facto state of the art. Nevertheless, Collins and Lanza (2010) cite that one advantage associated with Multiple Imputation is the ability to include cases where covariates are missing.

In my analysis, I use the Mplus MLR estimator, described above, which by default, uses both complete cases and those with partially missing data. Accordingly, because I am using a FIML approach to missing data, the parameter estimates I obtain should be unbiased and consistent.

3.4.7: Deciding on the Number of Latent Classes – Model Fit

To begin, there exists no single, universally applicable criterion by which the researcher can decide whether a latent class model should include *c* or $c \pm 1$ latent classes (Collins & Lanza, 2010; Magidson & Vermunt, 2004; Masyn, 2013; Nylund, Asparouhov, & Muthen, 2008). However, there do exist several well-studied fit indices, which taken together, and examined in light of the particular characteristics of the dataset and latent class model, can provide greater confidence that the *true* number of latent classes has been identified. Although one criterion of absolute fit exists (i.e., X^2_{LR}), researchers typically rely on several measures of relative fit (e.g., *BIC*, *CAIC)* when deciding on the number of latent classes Finally, if sample size permits, the researcher also could conduct a split sample cross-validation study to further bolster confidence in the decision on the number of latent classes (Collins & Lanza, 2010; Magidson & Vermunt, 2004)

3.4.7.1: Absolute fit

In the context of latent class analysis, the likelihood ratio chi-square goodness of fit test (G^2, L^2 or X^2_{LR}) compares the model estimated response patterns to the observed response patterns. Again, following notation from Collins and Lanza (2010), the equation for G^2 is as follows:

$$G^2 = 2\sum_{w=1}^{W} f_w \log\left(\frac{f_w}{\hat{f}_w}\right) \tag{8}$$

Where:

W = the number of response patterns

f_w = the observed frequency of response pattern w

$\hat{f}_w$ = the model-estimated frequency of response pattern w

and is distributed chi-square with degrees of freedom given by;

$$df = W - P - 1$$

Where:

W = the number of response patterns

P = the number of parameters estimated, i.e., the number of latent class prevalences (γ_c ’s) and item-response probabilities (ρ_j ’s)

In the case of missing data, the G^2 statistic not only reflects the degree to which the data fit the model, but also the degree to which missing data depart from the assumption of MCAR. Therefore, in the presence of missing data, the G^2 statistic is adjusted to exclude the portion of the test statistic that represents missingness (Collins & Lanza, 2010).

Unlike standard reject-support contexts where model fit is obtained by rejecting the null hypothesis, hypothesis testing in the context of latent class analysis, as in the case of structural equation modeling, represents an accept-support context wherein model fit is supported when the researcher fails to reject the null hypothesis (Collins & Lanza, 2010; Kline, 2005).

While there is renewed interest in the general structural equation modeling community to place greater emphasis on absolute fit statistics (i.e., G^2), there are at least two limitations associated with using the likelihood ratio chi-square goodness of fit test in the context of latent class analysis. First, it is unclear whether the G^2 test statistic actually follows a chi-square distribution when the data are sparse (i.e., when a significant number of response patterns are observed with low frequency), thus rendering associated p values untrustworthy (Agresti, 2013). Second, even if G^2 were distributed chi-square, it is a well-known fact that G^2 is sensitive to sample size. As a result, simply by increasing sample size, the researcher risks increasing the likelihood of committing a Type I error (Masyn, 2013).

Notwithstanding the above caveats, I examine the significance of the adjusted likelihood ratio chi-square goodness of fit test in the context of my sample size, which is quite large, and the evidence from other soon to be discussed measures of relative fit.

3.4.7.2: Relative fit: Information Criteria

Information criteria provide a means of comparing the relative fit between several competing nested or unnested statistical models. In general, information criteria attempt to balance the degree of model fit, as represented by the maximized log likelihood, with model complexity or the number of estimated parameters (Collins & Lanza, 2010; Masyn, 2013; Vrieze, 2012). For example, in the case of latent class analysis, the researcher may increase the log-likelihood simply by extracting additional latent classes. However, while not ignoring the importance of model fit, information criteria penalize the over extraction of latent classes, thus striving for the most parsimonious solution.

Although several information criteria exist to help in deciding on the number of latent classes, there are four related criteria that have been studied extensively and are used often in practice. The four information criteria are:

-Bayesian Information Criteria (Schwarz, 1978):

$$BIC = -2LL + d\log(n) \qquad (9)$$

- Adjusted Bayesian Information Criterion (Schwarz, 1978; Sclove, 1987) :

$$aBIC = -2LL + d\log((n+2)/24) \qquad (10)$$

-Akaike's Information Criterion (Akaike, 1987; Akaike, Petrov, & Csaki, 1973):

$$AIC = -2LL + 2d \qquad (11)$$

-Consistent Akaike's Information Criterion (Bozdogan, 1987)

$$CAIC = -2LL + d([\log(n) + 1] \qquad (12)$$

Where in all cases:

LL = the maximized log likelihood function value

d = the number of parameters estimated in the model

n = the sample size

With respect to all four information criteria, the model with the lowest value represents the "best" model.

Several simulation studies have examined which information criteria are more likely to select the correct number of latent class and under what circumstances. Nylund et al. (2008), in one of the most cited latent class simulation studies, found that across varying sample sizes, class sizes, and number of indicators used, *BIC* and to a somewhat lesser degree *aBIC* significantly outperformed *AIC* and *CAIC*. Although *CAIC* chose the correct number of latent classes more frequently than *AIC, BIC* and *aBIC* correctly identified the number of latent classes in nearly all cases where sample size was 1000. In general, *AIC* suggested more latent classes than were simulated, while *CAIC* suggested fewer, particularly when the class sizes were unequal.

In another comprehensive latent class simulation study, Swanson, Lindenberg, Bauer, and Crosby (2012) examined the relative performance of *AIC*, *CAIC*, *BIC*, and *aBIC* across varying sample sizes, class sizes, number of indicators, amounts and types of missing data, as well as between models where the assumption of local independence was met or not. Overall, the simulation study revealed that *aBIC* provided the greatest accuracy, followed by *BIC*, and *CAIC*; *AIC* performed poorly across all conditions. Moreover, the accuracy of *aBIC*, *BIC*, and *CAIC* increased with sample size, reaching nearly 100% accuracy with sample sizes of 2000. However, in the case where the assumption of local independence was violated and the sample size was 2000, both *aBIC* and *BIC* over-estimated the number of classes in more than 95% of the replications (Swanson et al., 2012).

Finally, Morgan (2014) conducted a latent class simulation study to assess the performance of various information criteria when both categorical and continuous indicators were used together. Like Swanson et al. (2012), Morgan (2014) found that *aBIC* most frequently chose the correct number of latent classes across varying sample sizes, class prevalences and combinations of categorical and continuous indicators. Although, as the ratio of continuous indicators to categorical indicators increased, the accuracy of *BIC* exceeded that of *aBIC*.

To decide on the number of latent classes in my analysis, I report each of the information criteria presented above. However, based on the results of the above cited simulation studies and the characteristics of my sample, I give more weight to the number of latent classes suggested by *BIC* and *aBIC*, and least to *AIC*.

3.4.7.3: Relative fit: Inferential tests

Given that the typical likelihood ratio test statistic for comparing two nested latent class models does not follow a chi-square distribution, it cannot be used to decide between models with k or k -1 latent classes (Collins & Lanza, 2010; Masyn, 2013; McLachlan & Peel, 2004). However, there are two alternative tests available to compare whether the improvement in fit between two models is statistically significant: (i) the adjusted Lo-Mendell-Rubin likelihood ratio test (LMR-LRT) (Lo, Mendell, & Rubin, 2001) and (ii) the parametric bootstrapped likelihood ratio test (BLRT)(McLachlan & Peel, 2004). The former analytically approximates the chi-square distribution, while the latter derives the sampling distribution empirically when comparing between latent models with k versus k-1 classes. When either test is statistically significant (e.g., $p < .05$), the model with k classes, rather than k-1 is the preferred model (Asparouhov & Muthén, 2012; Masyn, 2013; Nylund et al., 2008).

Referring again to the latent class simulation study conducted by Nylund et al. (2008), the parametric bootstrapped likelihood ratio test (BLRT) emerged as the most accurate predictor of the correct number of latent classes among all the information criteria tested and the LMR-LRT. The adjusted Lo-Mendell-Rubin likelihood ratio test, though not as accurate as the BLRT, seemed to consistently overestimate the number of classes. To this point, Nylund et al. (2008) suggests that the LMR-LRT could be useful in practice for identifying an upper bound on the number of latent classes, i.e., a non-significant p-value would indicate a low probability that more latent classes exist than indicated by this test.

In addition to examining the significance of the likelihood ratio chi-square goodness of fit test, and more importantly, the information criteria, I also report and consult the results of the adjusted Lo-Mendell-Rubin likelihood ratio test. While simulation studies suggest that perhaps the parametric bootstrapped likelihood ratio test (BLRT) is the best overall means of deciding on the correct number of latent classes, it is not available in Mplus 7.3 when design weights are in use. As described above, to account for the complex nature of my sample, in conjunction with TYPE=COMPLEX MIXTURE, I also use STRATIFICATION=Strata name, CLUSTER=PSU, and WEIGHT= BTW000, which prohibits the use of the BLRT. Consequently, I am unable use BLRT as one means of deciding on the number of classes.

3.4.8: Classification Quality

While not to be used to assess model fit, the researcher may evaluate the potential utility of the model by assessing the degree to which the latent class model accurately classifies individuals based upon their posterior class probabilities (Masyn, 2013). Following the notation of Collins and Lanza (2010), posterior class probabilities may be obtained as follows:

$$P(L=c \mid Y=y) = \frac{P(Y=y \mid L=c)P(L=c)}{P(Y=y)} \tag{13}$$

Where:

$$P(Y=y) = \sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)}$$

$$P(Y=y \mid L=c) = \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)} \tag{14}$$

$$P(L=c) = \gamma_c$$

$$P(L=c \mid Y=y) = \frac{\left(\prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)} \right) \gamma_c}{\sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)}} \tag{15}$$

From equation 13, a vector of probabilities associated with belonging to each latent class for each individual is obtained.

Based on posterior class probabilities, relative entropy provides an overall measure of classification precision ranging from 0 to 1, with numbers closer to 1 representing greater classification precision (Ramaswamy, DeSarbo, Reibstein, & Robinson, 1993) While there is not a statistical test associated with entropy , Clark (2010) suggests that entropy values of .8 are considered high, .6 are moderate and .4 are low. Relative entropy is calculated as follows:

$$E = 1 - \frac{\sum_{i=1}^{n} \sum_{c=1}^{C} -p_{ic} \log p_{ic}}{n \log C} \quad (16)$$

Where p_{ic} = individual *i*'s posterior probability of membership in latent class *c* (Collins & Lanza, 2010).

Though relative entropy is a useful metric to assess the overall classification precision, Masyn (2013) notes that even with entropy levels near 1.0, there may be significant misclassification in some classes for particular individuals. To further identify where misclassifications may exist, Collins and Lanza (2010); Masyn (2013) suggest examining the average posterior class probability for each modally assigned individual in each latent class. The average posterior class probability is the mean of the posterior probabilities of all cases assigned to class *c* based on their maximum posterior probability. Nagin (2005) suggests that well classified latent classes have average posterior class probabilities > .7.

Another measure of specific latent class assignment precision is offered by the Odds of Correct Classification (Nagin, 2005);

$$OCC_c = \frac{AvePP_c / (1 - AvePP_c)}{\hat{\gamma}_c / (1 - \hat{\gamma}_c)} \quad (17)$$

Where $AvePP_c$ is the average posterior class probability for class *c* and $\hat{\gamma}_c$ is the model estimated latent class prevalence for class c. When $AvePP_c$ becomes large relative to the estimated probability that a randomly selected case would be assigned to class *c*, that is, $\hat{\gamma}_c$, the odds of correct classification increase. Nagin (2005) suggests that OCC_c values greater than 5 suggest well separated classes and good class assignment precision.

Although I do not use relative Entropy or average posterior class probability to assess model fit, I report these measures to assess the quality of classification, which is substantively relevant to my research questions. Because I use latent class membership as a latent variable in the eventual structural model, the degree to which cases are misclassified may affect the degree to which the conclusions I reach based on latent class membership are internally and externally valid. Mplus 7.3 provides Relative Entropy and average posterior class probabilities by default when using TYPE=MIXTURE (COMPLEX).

3.4.9: Measurement Invariance

Ideally, as in all cases of measurement, in order to make comparisons across groups in subsequent structural models, the latent class measurement model should be invariant across subpopulations. Although a robust measurement invariance research literature exists with respect to traditional factor analysis, and particularly in the case of Item Response Theory (IRT) (De Ayala, 2009; Hambleton, Swaminathan, & Rogers, 1991; Muthen & Lehman, 1985; Rudas & Zwick, 1995; Stark, Chernyshenko, & Drasgow, 2006; Teresi et al., 2007; Zwick, Donoghue, & Grima, 1993), there are fewer resources and studies that discuss or examine latent class measurement invariance. One notable exception is provided by Collins and Lanza (2010), who define latent class measurement invariance as follows:

> In LCA, an instrument fulfills measurement invariance across populations when individuals who belong to the same latent class, but who are from different populations, have the same probability of providing any given observed response pattern. (p. 117-118)

Typically, testing for measurement invariance involves assessing three increasingly restrictive types of invariance: (i) *configural*, (ii) *metric*, and (iii) *scalar* invariance (Millsap, 2012). In the context of latent class analysis, *configural* invariance holds when the same number of latent classes are found across subpopulations (Kankaraš, Moors, & Vermunt, 2010). To assess configural invariance, the researcher tests the latent class model within each subgroup. If, based on the above mentioned fit indices, the same number of latent classes are suggested within each group, the researcher can move to a test of metric or scalar invariance (Collins & Lanza, 2010; Kankaraš et al., 2010).

Having established configural invariance, the researcher may proceed to assess *metric* invariance, which implies that the relationships between the latent variable and the indicators are at least the same across groups. In other words, although the conditional item response probabilities may vary across groups, this variation does not depend on latent class. Specifically, metric invariance allows for direct effects of the grouping variable on an item, but these effects are constrained to be equal across latent classes.

Finally, Kankaraš et al. (2010) suggests that, in the context of latent class models, *scalar* invariance implies that the relationships between the latent variable and observed indicators are the same across groups *and* the conditional item response probabilities are also equal across groups. This implies that no direct effects exist between covariates and indicators, given the latent variable.

To test varying levels of measurement invariance, the researcher may compare the fit of a model where item response parameters are constrained to be equal across groups to one where item response parameters are estimated freely. Various degrees of partial measurement invariance may also be tested by constraining individual parameters across groups within all or selected latent classes (Collins & Lanza, 2010). In addition to examining information criteria to decide between unconstrained and constrained models, the researcher may also examine the significance of a likelihood ratio difference test statistic. This formula is calculated as

$$TRd = -2(L0 - L1)/cd \tag{18}$$

Where:

$L0$ = Log likelihood of the unconstrained model

$L1$ = Log likelihood of the constrained model

$cd = (p0 \cdot c0 - p1 \cdot c1)/(p0 - p1)$

$p0$ = # of parameters in the unconstrained model

$p1$ = # of parameter in the constrained model

$c0$ = scaling correction factor for the unconstrained model

$c1$ = scaling correction factor for the constrained model

I assessed the measurement invariance of my latent class model across Gender, Minority Status, and First-Generation College Status. First, I fit six separate latent class models, one within each category of the three binary covariates. I examined all of the above mentioned fit indices to determine if the same number of latent classes (*configural invariance*) was suggested within each subgroup. Next, using the KNOWNCLASS option in Mplus 7.3, I estimated and compared models where the conditional item response probabilities were constrained to be equal across groups to models where they were freely estimated. I compared *BIC* and other information heuristics between constrained and unconstrained models. In addition, I examined if the improvement in fit between the two models, based on the likelihood ratio difference test statistics (as described in equation 18), was statistically significant.

Finally, I tested whether there were direct effects between my three covariates and any indicators, conditional on the latent variable. In Mplus 7.3, this is accomplished by regressing the latent class and each indicator (separately) on each covariate.

3.5: Introduction to Factor Analysis

As mentioned previously, I posit that by factor analyzing the four ordinal variables that NCES used to create an index of academic integration (BPS: 04/09 “Academic

Integration index 2004"), the previously measurement-error attenuated relationship between the common or true score variance in student engagement and transfer may emerge.

Attributed to Spearman (1904, 1927), factor analysis attempts to identify the underlying, unobserved constructs that both influence and account for the correlations among a set of observed indicators. Further, the common factor model (Thurstone, 1947; Thurstone, 1954) posits that each manifest indicator is a linear function of at least one common factor and one unique factor. Accordingly, factor analysis partitions the variance in each indicator into two parts: the *common variance* (or true score variance), which is the portion of variance that is shared among indicators and explained by the latent construct, and the *unique variance* (or error variance), which consists of both unexplained, reliable indicator-specific systematic variance as well as unreliable random measurement error variance (Brown, 2014).

The basic factor model to describe person i's score on continuous indicator variable j can be expressed as:

$$x_{ij} = u_j + \lambda_{j1} z_{i1} + \lambda_{j2} z_2 + \lambda_{jm} z_{im} + u_{ij} \qquad (19)$$

Where:

x_{ij} is person i's score on indicator j

u_j is the intercept or score when all z_i's equal 0

$\lambda_{j1}, \lambda_{j2} ... \lambda_{jm}$ are the factor loadings of indicator j on factors 1…m

$z_{i1}, z_{i2} ... z_{im}$ are the common factor scores for person i on factors 1…m

u_{ij} is the factor score for person i on unique factor j

In matrix notation, the general factor model can be expressed as follows:

$$x = \Lambda_x \xi + \delta \qquad (20)$$

Where;

Λ_x is a matrix of factor loadings

ξ is a matrix of factor scores with a covariance matrix of Φ

δ is a matrix of residual errors (unique variates or factors) with a covariance matrix Θ_δ

(Green, Camilli, Elmore, & American Educational Research, 2006)

To elucidate the above equations, an example of a two factor confirmatory factor analysis is presented below in matrix format:

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix} = \begin{bmatrix} \lambda_{11} & 0 \\ \lambda_{21} & 0 \\ \lambda_{31} & 0 \\ 0 & \lambda_{42} \\ 0 & \lambda_{52} \\ 0 & \lambda_{62} \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \end{bmatrix} \qquad (21)$$

Specifically, given six observed variables with two presumed factors, indicators x_1, x_2, x_3 are presumed to load only on factor ξ_1 with loadings $\lambda_{11}, \lambda_{21}, \lambda_{31}$ while indicators x_4, x_5, x_6 are presumed to load only on factor ξ_2 with loadings $\lambda_{42}, \lambda_{52}, \lambda_{62}$. Additionally, the equation above contains one residual error matrix δ_k for each x_i. Further, fixing the factor loadings x_1, x_2, x_3 on ξ_2 and indicators x_4, x_5, x_6 on factor ξ_k to 0 demonstrates the researcher's hypothesis that these indicators (where $\lambda_k = 0$) are not reflective of factor ξ_k.

(Green et al., 2006)

3.5.1: Confirmatory Factor Analysis

Because the indicators and construct of engagement has been researched extensively by NCES researchers, I have an a priori notion that the four items identified by NCES to create their index of student engagement are potentially reliable indicators of academic engagement and that only one common factor exists. Therefore, I do not begin my analysis with an exploratory factor analysis (EFA).

Exploratory factor analysis (EFA) is, as the name implies, exploratory, allowing the data to drive the analysis without any a priori restrictions on the number of factors or the pattern of relationships among the observed indicators and latent factors. In my analysis, I posit only one factor measured by four observed indicators. When maximum likelihood estimation is used, the number of parameters associated with extracting more than one factor with only four observed indicators exceeds the information in the correlation matrix, and is therefore not identified (Brown, 2014). Moreover, while a confirmatory factor analysis model with two correlated factors, each with only two indicators is identified, Kline (2005), nevertheless, recommends a minimum of three indicators per factor to avoid estimation problems.

Given both the substantive and statistical reasons for extracting only one factor to represent academic engagement, decisions rules for deciding on the number of factors, choice of rotation, etc. are irrelevant in my case. As a result, I proceed directly to a confirmatory factor analysis.

3.5.2: Factor Analysis of Categorical Data

NCES researchers use four, three-category (Never, Sometimes, Often) ordinal indicators to create an index of student academic integration. As mentioned, I selected the same observed indicators to reflect my latent variable version of academic integration. As is well known, because categorical data do not meet the assumptions of traditional maximum likelihood estimation, factor analysis of categorical indicators using traditional maximum likelihood estimation may result in attenuated correlations among indicators, extraction of spurious factors representing item extremeness (difficulty), and incorrect standard errors and test statistics (Brown, 2014; Kline, 2005).

Although Maximum Likelihood estimation with numerical integration is a viable, yet computationally demanding approach to address non-continuous, non-normal indicators, I chose the robust Weighted Least Squares (WLSMV) estimator available in Mplus 7.3. In the case of factor analysis with categorical indicators, Flora and Curran (2004) demonstrated that WLSMV provides accurate test statistics, parameter estimates, and standard errors across a variety of sample sizes and conditions.

Not only does factor analysis of categorical indicators require a different method of estimation, but also the framework and steps involved differ from the case where the observed indicators are continuous and normally distributed. Specifically, the matrix analyzed in the case of categorical indicators is a correlation matrix rather than a covariance matrix. In the case of ordinal observed indicators, the correlation matrix is a polychoric matrix.

More importantly, in the case of categorical observed indicators, Mplus 7.3 employs Muthén and Asparouhov (2002) latent continuous response variable framework. Essentially, this framework posits an underlying latent continuous trait or ability, y^*, which represents a more discriminating level of the trait or ability than can be measured from dichotomous or ordinal indicators. Rather than using the actual polychoric correlations of observed categorical indicators, the correlations of the continuous y^* variables that caused the observed data are analyzed. The y^* variables are related to the observed categorical indicators through item thresholds (τ), which represent the value of y^* , where, if exceeded, in the case of a binary item, the observed y would equal 1, otherwise 0 (Brown, 2014; Kline, 2005).

Because the actual variances of the indicators are not analyzed, in the most common scaling of the y^*, referred to as the *delta parameterization* in Mplus, the residual variances of the categorical indicators are not free parameters, but rather are obtained by subtracting the squared standardized factor loading from 1. An alternative scaling, referred to as the *theta parameterization*, is akin to Item Response Theory parameterization. In my analyses, I use the *delta parameterization* because my research questions are less interested in item characteristics. Moreover, because all the items were measured using the same method, method effects should not exist. Likewise, there is no substantive theory that would suggest the need for correlated error terms.

3.5.3: Indicator Adequacy

Given that I extract only one latent factor, I judge the quality of the selected observed indicators in terms of the magnitude of their factor loadings, which represent the standardized estimate of the regression of the y^* variables on the latent factor. In line with Kline (2005), I consider standardized factor loadings greater than .3 as acceptable. I also square each factor loading to obtain *r-squared* values, which express the proportion of variance explained in the y^* variables, which are related to the observed variable through the thresholds (τ), by the latent factor. Finally, I also assess the standardized bivariate residual correlations between items, noting any values significantly greater than 2.

3.5.4: Model Fit Statistics and Indices

As in the case of Latent Class Analysis, assessment of the Model-Data fit of a latent factor analysis is typically assessed by: (i) a hypothesis test of the exact fit between the model implied covariance matrix Σ and the observed sample covariance matrix S, which in this case is a correlation matrix based on the y^* variables , and (ii) an examination of an ever-growing list of approximate fit indices.

As prefatory, Kline (2005) concedes that the assessment of the utility of a latent variable model requires much more than assessing the fit between the model and the data. First, because the goal in latent variable modeling is to obtain parameters estimates that minimize the discrepancy between the model implied Σ and the observed S covariance structures (*y** in my case), the researcher can obtain near perfect model fit simply by reducing the df_M (i.e., allowing all parameters to be free). Second, even if a model fits the data well and appears to be correctly specified according to substantive theory, this only provides evidence that the specified model is plausible; it does not prove that the model is superior to other possible equivalent or nearly-equivalent models that fit the data equally well (MacCallum & Austin, 2000; MacCallum, Wegener, Uchino, & Fabrigar, 1993).

Beginning with the exact-fit hypothesis test, the null hypothesis states that the model implied covariance matrix and the observed covariance matrix are equivalent, whereas the alternative hypothesis states that Σ and S are different ($H_0 : \Sigma = S$; $H_a : \Sigma \neq S$) Therefore, unlike standard reject-support contexts where model fit is obtained by rejecting the null hypothesis, hypothesis testing of the overall latent variable model represents an accept-support context wherein model fit is supported when the researcher fails to reject the null hypothesis (Kline, 2005).

With the aforementioned caveats in mind, the most common exact fit test is the mean and variance adjusted likelihood ratio chi-square test (Muthén & Muthén, (1998-2012)). Accordingly, if the p-value is greater than the selected α level (e.g., .05), then the null hypothesis is not rejected and the researcher concludes that any discrepancy between Σ and S is the result of chance. As a final note, the χ^2 test, as previously mentioned is sensitive to sample size such that when the sample size is large even very small differences between Σ and S will result in a rejection of the null hypothesis.

Although there are numerous approximate fit indices, I rely primarily on the following given the nature of my data and a review of the literature:

(1) Root mean square Error of Approximation (RMSEA)

(2) Comparitive Fit Index (CFI)

(3) Tucker-Lewis Index (TLI)

The Root Mean Square Error of Approximation (Steiger & Lind, 1980) is a badness of fit index that rewards a model for parsimony and increased sample size:

$$RMSEA = \sqrt{\frac{\chi_M^2 - df_M}{df_M (N-1)}} \tag{22}$$

Where:

χ_M^2 is the model chi-square value

df_M is the model degrees of freedom

N is the sample size

From equation 22, it is obvious that increasing the model degrees of freedom df_M, all things being equal, will decrease the value of the numerator and increase the value of the denominator resulting in a smaller value of RMSEA. However, as the sample size becomes large, the effect of the penalty for model complexity is attenuated. RMSEA levels below .10 are typically regarded as reasonable, whereas RMSEA levels below .05 are purportedly reflective of good model fit (Browne, Cudeck, Bollen, & Long, 1993) . Finally, RMSE is hypothesized to roughly follow a noncentral chi square distribution, which allows the calculation of a confidence interval around the RMSEA estimate.

RMSEA is an example of an absolute fit index, whereas the Bentler Comparative Fit index (CFI) (Bentler, 1990) and the Tucker-Lewis Index (TLI) (Tucker & Lewis, 1973) are examples of comparative fit indices that reflect the relative improvement in model fit that results from the researcher's model over the baseline or independent model. The basic formulas for *CFI* and *TLI* are as follows:

$$CFI = 1 - \frac{\chi_M^2 - df_m}{\chi_B^2 - df_B} \tag{23}$$

$$TLI = \frac{\dfrac{\chi_B^2}{df_B} - \dfrac{\chi_M^2}{df_M}}{\dfrac{\chi_B^2}{df_B} - 1} \tag{24}$$

Where:

χ_M^2 is the chi-square non-centrality parameter for the researcher's proposed model
df_m is the researcher's model degrees of freedom
χ_B^2 is the chi-square non-centrality parameter for the baseline model
df_B is the baseline degrees of freedom

The baseline model is typically constrained to be the independence model in which the covariances among observed variables are assumed to be zero. However, Kline (2005) criticizes this assumption as unlikely to be the case in reality, thus rendering comparisons of models to independence models of dubious utility. In response, Widaman and Thompson (2003) have suggested the use of baseline models that are more realistic (e.g., models where at least some observed variables are assumed to covary to some degree).

Notwithstanding this potential limitation, Brown (2014) suggests that both *CFI* and *TLI* are among the best behaved of the existing fit indices. From the formulas above, it is evident that both indices compare the proposed model to the baseline model, but TLI, like RMSEA, also exacts a penalty for complex models that do not concomitantly increase model fit. Values of *CFI* vary from 0 to 1, whereas TLI values may fall outside 0 and 1. In both cases, values above .95 indicate well-fitting models (Hu & Bentler, 1999).

In sum, I assessed the fit of my confirmatory factor analysis model by examining the significance of the mean and variance adjusted likelihood ratio chi-square test, and by examining the values of the fit indices in relation to the recommended cut offs.

3.5.5: Measurement Invariance

As in the context of the latent class model, if the latent variable measurement model is to be used in a broader structural model, it is important to establish that the latent variable measurement model is invariant across subgroups. As above, I assess measurement invariance across Gender, Minority status, and First-Generation college status.

Because the observed indicators are categorical, and in keeping with the above mentioned latent response variable framework, the variances of the y^* variables, known as *scale factors*, contain information about residual variance, factor loadings and factor variance, and can be compared in a multiple group analysis.

In the case of factor analysis, *configural* invariance is achieved when the same number of factors and general pattern of relationships holds across groups. *Metric* invariance implies that the factor loadings are equivalent across groups. Finally, *scalar* invariance is observed when item intercepts are invariant across groups. In other words, *scalar* invariance implies that individuals with the same value of the underlying latent construct, should have equal values on the observed variables. Or, in my specific case, the values of thresholds should be the same across groups.

Because factor loadings and thresholds depend on each other in the latent variable modeling framework, *metric* and *scalar* invariance must be tested simultaneously (Muthén & Asparouhov, 2002). To compare between unconstrained and constrained models, the researcher can assess the significance of a corrected likelihood ratio difference test statistic.

In Mplus 7.3, *configural*, *metric* and *scalar* invariance can be assessed by specifying MODEL =*configural metric scalar* in the analysis section of the code. This command in conjunction with the GROUPING=”Covariate” command provides corrected likelihood ratio difference test statistics, which I use to assess measurement invariance across the three covariates in my model.

3.6: Traditional Approaches to Latent Class Structural Models

Having described the two latent variable measurement models, I now turn to a discussion of the steps I took to construct and test the proposed structural latent class regression model. In essence, my conceptual model contends that covariates influence latent class membership, and, in turn, latent class membership, not only affects distal outcomes, but also moderates the relationships between other auxiliary variables and transfer. In this section, I introduce a basic latent class model with covariates and one with both covariates and distal outcomes. I also discuss potential drawbacks associated with traditional approaches to latent class regression. Second, I introduce the improved method used in this study, as well as describe the steps I took to build and assess the final structural models.

When estimating conditional latent class models with covariates and distal outcomes like the one described above, researchers historically have employed one of two approaches, both of which, under different circumstances and research objectives, may not provide the desired results.

3.6.1: Classify-Analyze Approaches

First, in what is often referred to as the classify-analyze approach (Clogg, 1995), the researcher conducts an unconditional latent class analysis and classifies individuals into their most likely latent class based on their maximum posterior probabilities. Second, latent class membership is treated as an observed categorical variable in subsequent structural models.

Within the latent class framework, individuals often have non-zero probabilities of belonging to two or more classes. This uncertainty or measurement error in latent class assignment is accounted for in subsequent analyses conducted within a latent structural model. However, within the analyze step of a classify-analyze approach, latent class assignment is treated as known and therefore perfectly reliable. As mentioned previously, structural regression models assume that variables have been measured without error. Consequently, the degree to which latent class assignment is unreliable, subsequent observed relationships with other distal outcomes will be attenuated (Bolck, Croon, & Hagenaars, 2004; Vermunt, 2010). Therefore, unless classification accuracy is nearly perfect (e.g., Entropy levels nearing 1.0), the classify-analyze approach will produce negatively biased estimates of the structural relationships.

3.6.2: One-Step Approach

The second traditional means of incorporating latent class variables into a larger structural model is referred to as the 1-step approach. As the name implies, in this approach, the researcher jointly estimates in one step the latent class measurement model and the structural associations between covariates, latent classes, and distal outcomes. Unlike the classify-analyze approach, the 1-step approach produces unbiased structural parameter estimates, reflective of the measurement error-corrected latent classes (Asparouhov & Muthén, 2013, 2014a; Vermunt, 2010).

However, Vermunt (2010) notes several potential drawbacks associated with the practical application of the 1-step approach. First, with respect to covariates, researchers typically estimate an unconditional measurement model first, and introduce covariates in a second stage. On the one hand, Nylund and Masyn (2008) showed via simulation study that including misspecified covariates in the initial measurement model can lead to bias in the number of classes identified. On the other hand, with respect to the structural parameter estimates of the relationships between latent class and covariates, Clark and Muthén (2009) demonstrated that, unless entropy is greater than .8, the 1-step approach produced significantly less biased estimates than classify-analyze approaches.

Nevertheless, while the 1-step approach provides unbiased estimates of the relationships between covariates, latent classes, and distal outcomes, Asparouhov and Muthén (2014a) note that the 1-step approach may change the meaning of the latent class model. For example, in the traditional one-step approach, distal outcomes predicted by latent class membership function, essentially, as additional indicators in the latent class model. Consequently, the meaning of the latent class may change, reflected by differences in latent class prevalences, conditional item probabilities and classifications between the initial unconditional model and the subsequent latent class model estimated jointly with auxiliary variables (Petras & Masyn, 2010).

Again, following Collins and Lanza (2010) a latent class regression with one covariate and no direct effects from covariates to indicators, may be expressed as follows:

$$P(Y = y \mid X = x) = \sum_{c=1}^{C} \gamma_c(x) \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j = r_j)} \tag{25}$$

Where X is a covariate and $\gamma_c(x)$ is the probability of falling in latent class c given covariate value x:

$$\gamma_c(x) = P(L = c \mid X = x) = \frac{e^{\beta_{0c} + \beta_{1c}x}}{1 + \sum_{c'=1}^{C-1} e^{\beta_{0c} + \beta_{1c}x}} \tag{26}$$

In this case, $\gamma_c(x)$ is a multinomial logistic model where the intercept, $e^{\beta_{0c}}$, represents the odds of membership in latent class c compared to the reference class C when covariate $X = 0$. Similarly, the slope coefficient, $e^{\beta_{1c}}$, represents the change in the odds of membership in latent class c compared to the reference class C associated with a one-unit change in X. Because one class is treated as the baseline referent, there will be $C - 1$ intercepts and slopes associated with each covariate (Collins & Lanza, 2010).

As mentioned above, when the standard 1-step approach is employed to estimate the effect of latent class membership on a distal outcome, the distal outcome functions essentially as an additional indicator within equation 25 above (Huang, Brecht, Hara, & Hser, 2010; Muthén, 2004).

3.6.4 Three-step Approach

Given that, for different reasons, neither the classify-analyze nor the 1-step approach to latent class structural equation modeling is appropriate in most applied cases, alternative approaches have been developed that combine the positive aspects of the two traditional approaches, while avoiding the aforementioned drawbacks. While there are varying derivations of the formula and processes involved in *three step approaches*, and different recommendations based on the kinds of models and types of data involved, I focus primarily on the solution provided by Asparouhov and Muthén (2014a), which is based on work by Bolck et al. (2004) and later Vermunt (2010).

In the first step, the researcher conducts an unconditional latent class model without covariates or distal outcomes. In the second step, each case is assigned to the class for which the posterior probability is greatest; a nominal variable representing the most likely class is then created for each individual. Unlike classify-analyze approaches, an important part of this second step involves calculating the classification uncertainty for each of the nominal most likely class variables. In the third step, a new latent class model is specified in which the nominal variables act as indicators of the latent class with measurement error pre-fixed at the rates calculated in step two (Asparouhov & Muthén, 2014b). As a result, in any subsequent structural models, the unreliability of latent class assignment is accounted for, thus parameter estimates are unattenuated unlike in the classify-analyze approach, and the measurement model is constructed without influence of the auxiliary variables, thus, unlike the 1-step approach, retaining its original meaning.

Referencing Asparouhov and Muthén (2014b), the classification uncertainty can be calculated as follows:

$$q_{c_2,c_1} = P(\mathrm{N} = c_1 \mid C = c_2) = \frac{p_{c1,c_2} N_{c1}}{\sum_c p_{c2} N_c} \qquad (27)$$

Where N is the most likely class nominal variable, and p_{c1,c_2} is the average estimated posterior probability of being in class c_2, when assigned to most likely class c_1, and N_c is the number of cases assigned to the latent class. Finally, the logits of $q_{c_2,c_1} / q_{c_2,K}$ are calculated for each class, representing the measurement error associated with each latent class nominal indicator.

Several simulation studies have confirmed that the above mentioned three step approach provides unbiased estimates, and, when entropy levels are at least .6, is as efficient as the 1-step approach. However, in the case where there are direct effects of covariates on indicators, the three step approach was unable to absorb such misspecification. In these cases, it is recommended to include the direct effects in the initial latent class model (Asparouhov & Muthén, 2014a; Vermunt, 2010).

While the same simulation studies suggest that Lanza's (2014) method for predicting binary distal outcomes from latent class membership is superior, it currently is limited to only one distal outcome and no covariates (Asparouhov & Muthén, 2013, 2014a, 2014b). At larger sample sizes and moderate entropy, however, the performance of the three step approach was roughly equivalent to Lanza's method.

In Mplus 7.3, I followed these steps by first specifying the unconditional latent class analysis, checking for direct effects of covariates and incorporating them if warranted. I identified all auxiliary variables by listing them after the AUXILIARY variable command; I also evoked the SAVEDATA option to save the data with the nominal most likely latent class variable. Next, I opened the saved file from the first step and entered the misclassification logits that I had recorded from the section of the output entitled "Logits for the Classification Probabilities for the Most Likely Latent Class Membership (Row) by Latent Class." At this point, I could test any additional auxiliary model.

3.7: Structural models

3.7.1: Model 1:Latent Class Regression

First, to examine the relationship between student background variables and latent class prevalences, I regressed latent class membership on the three covariates in my model.

The general latent class regression is reflected in equation 28 and referred to as Model 1 in the results:

$$\gamma_c(x) = P(L = c \mid X = x) = \frac{e^{\beta_{0c} + \beta_{1c} GENDER + \beta_{2c} MINORITY + \beta_{3c} FIRSTGEN}}{1 + \sum_{c'=1}^{C-1} e^{\beta_{0c} + \beta_{1c} GENDER + \beta_{2c} MINORITY + \beta_{3c} FIRSTGEN}} \tag{28}$$

I assessed model fit by examining both the overall fit of the model using information criteria as well as the statistical significance of individual covariates. This analysis provides estimates of the relative odds of latent class membership as a function of the covariate values.

3.7.2: Model 2: Latent Class and Distals

In the next step, I regress the four observed and one latent distal outcomes on the conditional latent classes. Equation 29 provides simplified notation to communicate the basic model:

$$P(Distal = distal \mid L = c) = \frac{e^{\beta_{0c|X=x}}}{1 + e^{\beta_{0c|X=x}}} \tag{29}$$

Model 2 allows for a comparison of distal outcomes across the latent classes. Moreover, if the means and proportions of the distal outcomes vary in expected ways across the latent classes, such evidence can provide support for the criterion validity of the latent class solution. I assess the statistical significance of the differences among latent classes in the proportions and means of the distal outcomes by examining Wald test statistics.

3.7.3: Model 3: Latent Class-Specific Intercepts

Model 3 regresses transfer on the student background and student experience/academic performance variables, holding slopes constant across classes, but allowing the estimation of class-specific intercepts. Equation 30 describes Model 3:

(30)

$$P(TRANSFER = transfer \mid L = c) = \frac{e^{\beta_{0c|X=x} + \beta_1 FIRSTGEN + \beta_2 GENDER + \beta_3 MINORITY + \beta_4 GPA + \beta_5 REMED + \beta_6 ENGAGE}}{1 + e^{\beta_{0c|X=x} + \beta_1 FIRSTGEN + \beta_2 GENDER + \beta_3 MINORITY + \beta_4 GPA + \beta_5 REMED + \beta_6 ENGAGE}}$$

Model 3 examines the latent class conditional relationships between the aforementioned variables and transfer. This model assumes that the same relationships exist between the covariates and transfer. The intercepts reflect the differences in the average probability of transfer when all covariates are set to zero. Therefore, the same relationships in different classes will result in different predicted probabilities of transfer due to differences in the intercepts.

3.7.4: Model 4: Latent Class-Specific Intercepts and Slopes

Model 4 is identical to Model 3, with the exception that not only the intercepts, but also the slopes are allowed to vary across latent classes.

(31)

$$P(TRANSFER = transfer \mid L = c) = \frac{e^{\beta_{0c|X=x} + \beta_{1c} FIRSTGEN + \beta_{2c} GENDER + \beta_{3c} MINORITY + \beta_{4c} GPA + \beta_{5c} REMED + \beta_{6c} ENGAGE}}{1 + e^{\beta_{0c|X=x} + \beta_{1c} FIRSTGEN + \beta_{2c} GENDER + \beta_{3c} MINORITY + \beta_{4c} GPA + \beta_{5c} REMED + \beta_{6c} ENGAGE}}$$

Model 4 is an example of latent class moderation. Specifically, this model tests whether the relationships between the covariates and transfer are the same across classes. Model 4 is of most interest to the present study as this tests the hypothesis that the relationships between the covariates and transfer likelihood differ across latent subtypes.

CHAPTER 4: RESULTS AND DISCUSSION

This study explored both methodological and substantive issues pertaining to community college transfer to four-year institutions. Methodologically, this study examined the viability of using a latent class measurement model to classify students into hypothesized transfer subtypes. Further, using a relatively new unbiased three-step modeling approach described in chapter 3, this study also tested structural models in which covariates predicted latent class membership and latent class membership, in turn predicted distal outcomes. This appears to have been the first study of community college transfer (or any community college outcome) to use both a latent class approach and the three-step structural modeling technique.

Substantively, this study used latent class analysis as a means of classifying students into a small number of substantively different transfer subtypes. The proposed benefit to doing so lies in simplifying very complex arrays of variables into a manageable number of interpretable transfer subtypes. Further, this study explores whether three malleable variables, Engagement, Remediation, and first-year grade point average are predictive of transfer, conditional on latent class membership and student background variables. Finally, this dissertation assesses whether the relationships between these variables and transfer differ by latent class. If so, community colleges could provide transfer subtype specific advice and interventions that facilitate transfer to four-year institutions.

Organizationally, Chapter 4 begins with the results of the unconditional latent class model and a discussion of the findings. Second, I present and discuss the results of the latent class measurement invariance tests. Third, I present the results of the measurement model

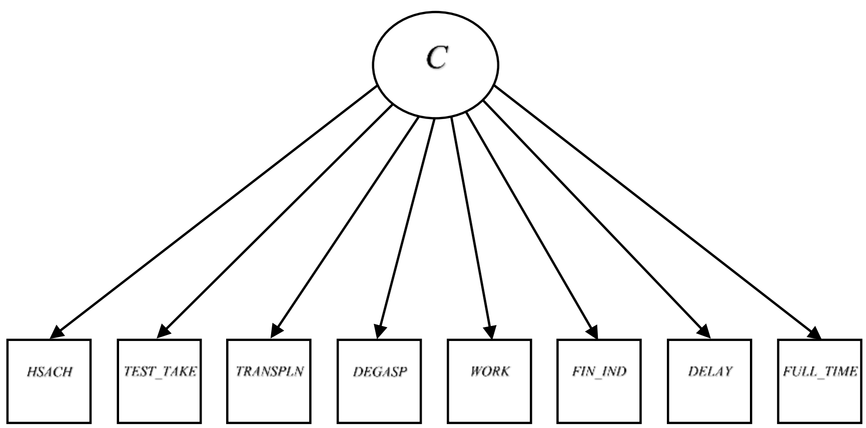
(CFA), and invariance tests for the latent student engagement factor. Fourth, I present and discuss the results of the four structural models introduced in chapter 3.

4.1: Unconditional Latent Class Analysis

The first research question I attempt to answer in this study is whether a latent class analysis can identify useful subtypes of transfer risk from students' statuses on several literature based correlates of transfer. First, based on my review of the literature, I chose observed latent class indicators from the domains indicated in my conceptual model: (i) Pre-collegiate Academic Resources, (ii) Transfer Intentions, (iii) External Demands, and (iv) Initial Academic Momentum. As mentioned in chapter 3, I tested several latent class models, with varying numbers of latent classes measured by different indicators and numbers of indicators. All analyses were conducted using Mplus 7.3.

The final unconditional latent class model that I tested is displayed in Figure 3.

Figure 3. *Unconditional Latent Class Model.*



I tested models with 1 to 7 latent classes. Table 13 displays the various fit statistics and indices associated with each candidate model.

Table 13: Latent Class Fit Statistics.

	LL	*npar*	Adj. χ^2_{LR} (df), *p* -value	*BIC*	*aBIC*	*AIC*	*CAIC*	*AWE*	Adj. LMR-LRT *p* -value (H_0: K classes ; H_1: K + 1 classes)	*Entropy**
1 class model	-23561.77	12	2263.87 (1283), < 0.01	47222.89	47184.76	47147.54	47237.94	47364.34	<0.01	
2 class model	-22836.39	25	1659.252 (1270), <0.01	45879.76	45800.32	45722.78	45911.12	46174.45	<0.01	0.556
3 class model	-22634.38	38	1457.278 (1257), <0.01	45583.35	45462.61	45344.75	45631.02	46031.28	**0.22**	0.643
4 class model	-22501.54	51	**1323.381 (1244), 0.06**	45425.30	45263.25	45105.08	45489.27	46026.47	0.27	0.760
4 class model (6 Direct Effects)	-22413.40	57	na	**45298.69**	**45117.57**	**44940.79**	**45370.19**	**45970.59**	0.38	0.752
5 class model	-22437.66	64	1257.349 (1231), 0.29	45405.17	45201.81	44940.45	45485.44	46159.57	0.77	0.720
6 class model	-22393.23	77	1210.455 (1218), 0.56	45423.93	45179.26	45128.94	45520.51	46331.57	0.31	0.643
7 class model	-22352.46	90	1166.407 (1204), 0.78	45450.03	45164.05	44884.93	45562.92	46510.91	0.77	0.690

Beginning with the adjusted chi-square likelihood ratio test, the first non-significant result was associated with the 4 class model χ^2 (51, *N* = 3490) = 1323.38, *p* >.05. For all analyses, unless otherwise stated, I used an alpha level of .05. Ignoring for the moment the 4 class model with direct effects, *BIC, AIC* and *CAIC* point to a 5-class model, whereas, *aBIC* continued to decrease even when 7 classes were extracted. At the other end of the spectrum, the adjusted Lo-Mendell-Rubin likelihood ratio test became non-significant χ^2_{LMR} (13, *N* = 3490) = 400.3, *p* >.05 when comparing the improvement between three and four class models, which suggests the 3-class model is superior.

Interestingly, two of the fit statistics that are prone to overestimating the number of latent classes, suggest fewer latent classes than the information criteria, which penalize complex models. As is well known, the adjusted chi-square likelihood ratio test is sensitive to sample size, and therefore prone to increasing type I errors. Given my relatively large sample size (N=3490), it was unexpected that the adjusted chi-square likelihood ratio test would suggest fewer classes (4) than the information criteria. Likewise, given that simulation studies conducted by Nylund et al. (2008) suggest that the Lo-Mendell-Rubin likelihood ratio test could be used to identify an upper limit on the number of classes, it was unexpected that this test would suggest the fewest classes (3) of any of the fit indices.

With respect to the information criteria, *BIC*, which simulation studies seem to support as perhaps the most accurate of the information criteria, reaches its nadir at 5 classes, but the difference between the 4 and 5 class models is trivial. *AIC*, which routinely overestimates the number of latent classes in simulation studies, suggests the 5-class model, while *CAIC* is content with either a 4 or 5 class model. Finally, *aBIC* continues to decline with each additional latent class.

The fact that *aBIC* continues to decline with each additional class could be an indication of local dependence. Specifically, in simulation studies, Swanson et al. (2012) showed that in 100% of replications, when items were locally dependent, *aBIC* overestimated the number of classes.

To check for violations of local independence, I examined the significance of the standardized bivariate residuals between each category of each indicator; the standardized bivariate residuals are normally distributed z scores. Five of the 174 standardized bivariate residuals exceeded 1.96. However, to account for the familywise error associated with testing 174 hypotheses, I chose a bonferroni adjusted critical value (z = 3.44) associated with the adjusted α of .05/174. None of the standardized bivariate residuals exceeded the adjusted critical value.

Consequently, based on the lack of statistically significant standardized bivariate residuals, it does not appear that the model violates the assumption of local independence. As a result, it is unclear why *aBIC* fails to reach a minimum even after 7 classes were extracted.

Taken as a whole, the indices appear to suggest either a 4 or 5 class model. The adjusted chi-square likelihood ratio test suggests 4 classes, while the Lo-Mendell-Rubin likelihood ratio test, which can be used as a gauge of the upper limit on the number of classes, suggests 3 classes. *CAIC* suggests either a 4 or 5 class model, while *AIC*, which tends to overestimate the number of classes, suggests 5. *BIC* suggests 4 or 5 classes, while *ABIC* suggests 7 or more classes.

Consequently, I limited my focus to models with 4 and 5 classes, examining each with respect to class sizes and potential substantive interpretability. Substantively, the 4 class model was preferable to the 5 class model. The additional class added in the 5 class model was small and uninterpretable. Therefore, based on both the somewhat inconsistent advice offered by the fit indices and substantive utility, I settled on a 4 class model.

4.1.1: Latent Class Prevalences and Item-Response Probabilities

Table 14 displays the estimated latent class prevalences (γ_c's) and conditional item-response probabilities (ρ_j's) for the unconditional latent class model with 4 classes. To aid in interpretation, I bolded the maximum item response probability for each item within each latent class; moreover, if the maximum item response probability was >.70, I also italicized the item response probability (Masyn, 2013).

To begin, estimated latent class prevalences (γ_c's) range from .12 in Class 2 to .52 in Class 1. In other words, based on the estimated posterior probabilities, the model estimates that 12% of first-time beginning community college students would be assigned to Class 2 and 52% to Class 1. Relatively speaking, Class 1 could be considered the normative class, while Class 2 could be considered somewhat rare. Fortunately, none of the classes are extremely small, and, given my sample size (N=3490), even the smallest class, based on modal class assignment, consists of 494 students.

Table 14. Conditional Latent Class Item Response Probabilities.

		Latent Classes			
		High Transfer Intentions, Few Barriers (Class 1)	Low Transfer Intentions, Some Barriers (Class 2)	Moderate Transfer Intentions, Low Academic Resources (Class 3)	Moderate Transfer Intentions, Low Academic Momentum (Class 4)
	Latent Class Prevalences	0.52	0.12	0.16	0.19
	Item Response Probabilities				
Academic Resources	High School Academic Rigor				
	Low	**0.44**	**0.61**	***0.72***	**0.64**
	Medium	0.23	0.25	0.25	0.21
	High	0.34	0.14	0.03	0.15
	Took College Admission Exams				
	Did not Take Exams	0.03	0.35	***0.99***	0.49
	Took Exams	***0.97***	**0.65**	0.01	**0.51**
Transfer Intentions	Degree Expectations				
	Below Bachelors	0.05	**0.68**	0.09	0.05
	Bachelors	0.39	0.33	0.38	0.41
	Above Bachelors	**0.57**	0.00	**0.53**	**0.54**
	Transfer Expectations				
	Do not Plan to Transfer	0.19	***1.00***	0.35	0.37
	Plan to Transfer	***0.81***	0.00	**0.66**	**0.63**
External Demands	Employment				
	Work full-time	0.17	0.29	0.11	**0.55**
	Work part-time	**0.62**	**0.48**	**0.62**	0.25
	Not Employed	0.21	0.23	0.27	0.20
	Financial Dependency Level				
	Independent with Dependents	0.03	0.17	0.02	0.19
	Independent	0.01	0.03	0.01	0.16
	Dependent	***0.96***	***0.80***	***0.98***	**0.64**
Academic Momentum	Delayed Postsecondary Entry				
	Delayed	0.10	0.44	0.32	***0.90***
	Did not Delay	***0.90***	**0.56**	**0.69**	0.11
	Enrollment Intensity				
	Part-time	0.16	0.39	0.33	**0.63**
	Full-time	***0.84***	**0.61**	**0.67**	0.37

With respect to latent class homogeneity and separation, beginning with Class 1, estimated conditional item response probabilities (ρ_j's) exceed .70 for TEST_TAKE, TRANSPLN, FIN_IND, DELAY, and FULL_TIME. Conversely, HSACH shows poor homogeneity for Class 1, while DEGASP and WORK exhibit moderate homogeneity.

With the exception of HSACH, the conditional item response probabilities in Class 1, though not ideal, do suggest one response pattern that is more likely.
Specifically, based on the estimated item response probabilities, students in Class 1 could be characterized as those with high probabilities of having high transfer intentions (TRANSPLN & DEGASP) and academic momentum (DELAY & FULL_TIME), relatively few external demands (WORK & FIN_IND), and relatively high levels of academic resources (HSACH & TEST_TAKE), particularly as measured by TEST_TAKE.

Class 2 shows less overall homogeneity, with the exceptions of items, TRANSPLN and FIN_IND, which both have item response probabilities >.70, and to a lesser degree, DEGASP with a maximum item response probability of .68. Nevertheless, despite the fact that several items show only moderate homogeneity in this case, students in Class 2 can be described as those with high probabilities of having extremely low transfer intentions. Comparing classes 1 and 2, both indicators of transfer intention show high degrees of both homogeneity and latent class separation.

Class 3, like Class 2, shows less homogeneity than Class 1, except with respect to HSACH, TEST_TAKE, FIN_IND, , all with item response probabilities >.70; and DELAY with an item response probability of .69. Clearly, students in class 3 have high probabilities of having low levels of academic resources as evidenced by items HSACH and TEST_TAKE. In fact, the model estimates that the probability of having taken a college admission exam for a student in class 3 is effectively 0. Moreover, comparing classes 3 and

1, the transfer intention indicators, particularly TEST_TAKE, exhibit both high homogeneity and latent class separation.

Finally, Class 4 has the fewest indicators that exhibit high homogeneity. Only one item, DELAY, has an estimated item response probability >.70. Still, Class 4 is interpretable primarily through the items that measure academic momentum, but also through the general pattern of responses and how they differ from the other classes, specifically with respect to external demands. Specifically, students in Class 4, have high estimated probabilities of having low academic momentum, particularly with respect to the item, DELAY. When comparing classes 1 and 4, the indicators measuring academic momentum show high latent class separation. Finally, notwithstanding that the item response probabilities did not reach the desired level of .70, Class 4 is distinguished from the other classes in the relatively higher estimated probability of working full-time , and the relatively lower probability of not being a dependent compared to all other classes.

In general, many of the conditional item response probabilities failed to exceed .70, as recommended by Masyn (2013). Two items in particular, DEGASP and WORK, showed relatively low levels of homogeneity and latent class separation. On the other hand, the item, FIN_IND, displayed high global homogeneity, yet relatively low latent class separation. Nevertheless, none of the indicators were at chance levels across all latent classes. Furthermore, all of the indicators showed at least some degree of latent class separation between at least two classes.

However, to ensure that retaining the above mentioned low quality indicators was warranted, I ran several models excluding one or more of the poor quality indicators, collapsing ordinal indicators into binary items, etc. In each case, the solutions became less interpretable, with less consistent fit statistics than the model that included these items.

Having closely examined the conditional item response probabilities and their variations across latent classes, 4 relatively clear, class specific profiles emerge. First, because of the strong associations between transfer intentions and eventual transfer, if this latent class model is to be of practical value, the classes must differ to some degree in the conditional item response probabilities regarding transfer intentions. To this point, classes 1 and 2 are clearly separated with respect to transfer intentions, while classes 3 and 4 are quite similar, yet distinct from both classes 1 and 2. Based on these differences, I begin the labeling of latent classes as follows:

Class 1: “High Transfer Intentions”

Class 2: “Low Transfer Intentions”

Class 3 & 4: “Moderate Transfer Intentions”

After examining the differences in transfer intentions, a scan of the remaining domains reveals that students in Class 1 have high probabilities of possessing high levels of academic resources and academic momentum with low probabilities of indicating high levels of external demands. Therefore, I add to the title of Class 1, “few barriers.” In fact, students in Class 1, based on the estimated item response probabilities, should have the greatest likelihood of transferring to a four-year institution.

Turning to Class 3, the estimated item probabilities indicate moderate levels of academic momentum and low levels of external demands similar to Class 1. However, what separates class 3 from the other classes is the high probability of having low academic resources as evidenced by the item response probabilities associated with HSACH and TEST_TAKE. Therefore, I add to the title of Class 2, “Low Academic Resources.”

Finally, Class 4 is similar to class 3 in terms of transfer intentions, and similar to Class 2 regarding academic resources, however, it is well separated from all classes by the high item response probabilities of having low academic momentum. Students in Class 4 have an estimated probability of .90 of delaying postsecondary entry and only .37 probability of enrolling full-time. Consequently, I add to the title of Class 4, “low academic momentum.”

In addition, students in Class 4, compared to all other classes, have the lowest estimated probability of being dependent (.64) and the highest probability of being independent with dependents (.19), and, at the same time, have the highest estimated probability of working full-time (.55). As noted in chapter 2, external demands are associated with lower academic momentum (Adelman, 1999, 2005a, 2006; Crisp & Nuñez, 2014; Dougherty & Kienzl, 2006; Nora, 2004). Therefore, it is not surprising that higher levels of external demands and lower levels of academic momentum would go together. Nevertheless, when I tested the assumption of local independence, there were not statistically significant residual correlations, conditional on latent class.

Returning to Class 2, besides low transfer intentions, no other specific characteristics clearly separate Class 2 from classes 3 and 4. However, beyond the differences in transfer intentions, Class 2 is dissimilar to Class 1 with respect to the remaining domains. Therefore, in addition to the title, “low transfer intentions,” I add “some barriers”.

In sum, without committing the naming fallacy or reifying the latent classes (Kline, 2005), I label the classes as discussed and displayed in table 14.

4.1.2: Classification Quality

To assess classification quality, I examined both global and class specific measures, which I introduced in chapter 3. Globally, as displayed in table 15, the relative entropy value for the 4 class model was .76, which is considered moderate (Clark & Muthén, 2009). That the relative entropy is less than .80, which Asparouhov and Muthén (2014a) suggest is a minimum for which classify-analyze strategies would be feasible, confirms the need to conduct my structural models using the 3-step approach described previously.

With respect to class-specific classification quality, table 15 displays latent class prevalences (γ_c) for reference, the average posterior class probabilities ($AvePP_c$), and the odds of correct classification (OCC_c) for each latent class.

Table 15. Latent Class Classification Quality.

	Prevalence	$AvePP_c$	OCC_c
Class 1: High Transfer Intentions, Few Barriers	0.52	0.94	14.15
Class 2: Low Transfer Intentions, Some Barriers	0.12	0.77	24.14
Class 3: Moderate Transfer Intentions, Low Academic Resources	0.16	0.79	18.79
Class 4: Moderate Transfer Intentions, Low Academic Momentum	0.19	0.82	18.69

Beginning with the $AvePP_c$, Class 1 possesses the greatest average posterior class probabilities (.94), whereas Class 2 has the lowest (.77). However, all of the classes have $AvePP_c$ values above the recommended minimum of .7, which indicates that my classes are relatively well separated and the classification accuracy is acceptable (Masyn, 2013; Nagin, 2005).

Finally, for all classes, the odds of correct classification (OCC_c) are all well beyond the minimum suggested value of 5 (Nagin, 2005), which again suggests that latent class assignment accuracy is high. For example, the OCC_c for Class 2 implies that the odds of classification based upon $AvePP_2$ are 24 times the odds of classification based on random assignment according to the model estimated latent prevalences γ_c .

Overall, the 4 class model is supported by the fit statistics, yields substantively interpretable latent classes, and provides relatively high classification accuracy based on the estimated posterior class probabilities.

4.1.3: Latent Class Measurement Invariance

In order to assess both the effects of covariates on latent class membership and the effects of latent class membership on distal outcomes, the latent class measurement model must have the same meaning for members of different subpopulations. As mentioned above, Collins and Lanza (2010) suggest that latent class measurement invariance holds when individuals in the same latent class, but from different subgroups, have the same model estimated item response probabilities.

As mentioned in chapter 3, the first step I took to establish measurement invariance was to conduct a separate latent class analysis for each category of the three covariates in my model: Gender, Minority Status, and First-Generation College Status. Specifically, using the SUBPOPULATION variable command in Mplus 7.3, I conducted separate analyses for Males, Females, White/Asian, Minority, First-Generation College Student, and Not First-Generation College. I estimated 3, 4, 5, and 6 class models for each subgroup in order to assess *configural* invariance.

After assessing 24 models in all, based upon an examination of the same fit statistics displayed in table 13, the four class model was supported across all the six of the subgroups.

Having established *configural* invariance, I next moved directly to the assessment of *scalar invariance*, which in terms of latent class analysis can be tested by comparing the fit of a model where the item response probabilities are constrained to be equal across groups to one where they are freely estimated across groups.

I used the KNOWNCLASS command in Mplus 7.3 to compare unconstrained and constrained models across Gender, Minority Status, and First-Generation College Status. I assessed improvement in model fit by examining the significance of a corrected Likelihood Ratio Chi Square difference test and by assessing changes in *BIC* across models. The model comparisons are presented in table 15.

Table 16. Latent Class Measurement Invariance.

		LL	***df***	***BIC***
Gender	Model 1: Unconstrained	-25100.09	100	51028.08
	Model 2: Constrained	-25223.65	52	50877.81
	$\chi^2_{TRd} = 86.93, df = 48, p < .05$			
Minority Status	Model 1: Unconstrained	-24897.40	100	50622.69
	Model 2: Constrained	-25026.65	52	50483.80
	$\chi^2_{TRd} = 111.81, df = 48, p < .05$			
First Generation Status	Model 1: Unconstrained	-24913.88	100	50655.65
	Model 2: Constrained	-24993.77	52	50418.04
	$\chi^2_{TRd} = 67.70, df = 48, p < .05$			

As illustrated in table 16, the difference between the unconstrained and constrained models, based on the adjusted likelihood ratio chi square difference test, was statistically significant (p<.05) in each case, suggesting that the measurement non-invariant models fit the data better . Conversely, *BIC* was lowest for the constrained models in each case, suggesting that the models in which measurement invariance is imposed provide a better fit to the data.

Following the advice of Kankaraš et al. (2010), I rely on *BIC*, rather than the likelihood ratio chi-square difference test when deciding whether measurement invariance should be assumed. Because the likelihood ratio chi-square difference test is sensitive to sample size, and given that my sample is relatively large (3400), the differences between the two models may be trivial. To be sure, I examined the item response probabilities across each subgroup to assess the degree to which the item response probabilities varied. While there were small differences in item response probabilities across groups within the same classes, the differences were trivial and, most importantly, did not change the meaning of the latent classes in any case.

4.1.4: Direct Effects on Indicators

Given that the item response probabilities for students in the same latent classes, but from different subgroups, were invariant within sampling error, I proceeded to test for any direct effects of covariates upon the indicators. This is an important investigation for my study, given that simulation studies suggest that the three step approach is unable to absorb, in the third step, the effects of a misspecified model in the first step (Asparouhov & Muthén, 2014a).

Essentially, if a covariate is associated directly with an observed indicator of the latent class variable, then the indicators are no longer locally independent given the latent class variable. That the indicators are correlated beyond the influence of the latent variable prohibits the correct estimation of the measurement model, unless the direct effect is included (Asparouhov & Muthén, 2014a). Consequently, when the direct effect is omitted, parameter estimates of the relationships among predictors and latent class, as well as between latent classes and distal outcomes are biased not unlike the case of an omitted variable in normal regression (Muthén, 2004).

Table 17 displays the estimated slope, standard error of the estimate, the test statistic, and associated p-value for the direct effect between each indicator and the three covariates in my model. Indicated by bold italics, there were six direct effects that were statistically significant ($p < .05$). Consequently, I included these direct effects when I estimated the final measurement model.

Table 17: Direct Effects from Covariates to Latent Class Indicators.

		Estimate	*S.E.*	*Est./S.E.*	*p-value*
HSACH	GENDER	0.14	0.09	1.53	0.13
	MINORITY	0.15	0.10	1.43	0.15
	FIRST_GEN	0.05	0.10	0.52	0.61
TEST_TAKE	GENDER	0.19	0.19	1.01	0.32
	MINORITY	0.11	0.20	0.55	0.58
	FIRST_GEN	0.33	0.19	1.76	0.08
DEGASP	GENDER	0.06	0.11	0.54	0.59
	MINORITY	-0.29	0.10	-2.81	0.01*
	FIRST_GEN	0.28	0.10	2.65	0.01*
TRANSPLN	GENDER	-0.22	0.14	-1.57	0.12
	MINORITY	-0.03	0.12	-0.24	0.81
	FIRST_GEN	0.39	0.14	2.80	0.01*
WORK	GENDER	0.04	0.10	0.33	0.74
	MINORITY	-0.25	0.12	-2.16	0.03*
	FIRST_GEN	0.03	0.09	0.33	0.74
FIN_IND	GENDER	-0.92	0.22	-4.25	0.00*
	MINORITY	0.75	0.18	4.29	0.00*
	FIRST_GEN	0.07	0.22	0.33	0.74
DELAY	GENDER	0.10	0.16	0.58	0.56
	MINORITY	0.14	0.16	0.87	0.39
	FIRST_GEN	-0.29	0.15	-1.93	0.05
FULL_TIME	GENDER	-0.11	0.11	-0.97	0.33
	MINORITY	0.02	0.12	0.18	0.86
	FIRST_GEN	0.08	0.13	0.62	0.53

*p <.05.

4.2 Confirmatory Factor Analysis

As described in chapter 3, I conducted a confirmatory factor analysis using the four observed indicators NCES uses to create their index of Academic Integration. I hypothesized that the index used by NCES reflects a single construct reflected by the four indicators: ENGINF, ENGOUT, ENGADV, ENGSTUDY. Table 18 provides various fit statistics for the confirmatory factor analysis.

Table 18. Model Fit Statistics for Confirmatory Factor Analysis.

	χ^2	*df*	*p-value*	*RMSEA*	*RMSEA CI*	*CFI*	*TLI*
Factor Model	2.38	2	0.30	0.007	(0.000 - 0.033)	1.000	0.999

The overall fit statistics were excellent, suggesting the model fits the data very well. First, the chi-square value was not statistically significant, $\chi^2(2, N = 3490) = 2.38, p = .30$, indicating that differences between the model implied covariance matrix and the sample covariance matrix (actually the correlation matrix of the y* variables) are trivial. Second, the values of *RMSEA* (0.007), *CFI* (1.000) and *TLI* (0.999) all indicate excellent model fit.

Table 19 displays standardized factor loadings (β), residuals variances as well as R^2 values for each observed indicator. All of the factor loadings (β) were greater than .4 and statistically significant ($p < .05$), which indicates that the relationships between the latent factor and the indicators (*y** variables) are strong. The R^2 values, which describe the proportion of variance in the indicators (*y** variables) accounted for by the latent variable, are equally strong. Finally, when using the delta parameterization with categorical indicators, residual variances, as explained in chapter 3, are not estimated, but rather are obtained by subtracting the R^2 values from 1.

Based on the fit statistics and the strength of the factor loadings, I conclude that the measurement model of the construct, which I refer to as Engagement, is acceptable.

Table 19. Standardized Factor Loadings and R^2 Values for CFA.

Observed Variable	Description	Standardized Factor Loading	R^2	Residual Variance
ENGINF	Indicates whether or how often the respondent had informal or social contacts with faculty members outside of classrooms and the office during the 2003-2004 academic year.	0.56	0.32	0.69
ENGOUT	Indicates whether or how often the respondent talked with faculty about academic matters outside of class time (including e-mail) during the 2003-2004 academic year.	0.68	0.46	0.54
ENGADV	Indicates whether or how often the respondent met with an advisor concerning academic plans during the 2003-2004 academic year.	0.77	0.59	0.41
ENGSTUDY	Indicates whether or how often the respondent attended study groups outside of the classroom during the 2003-2004 academic year.	0.51	0.26	0.74

4.2.1: Measurement Invariance

As with the latent class analysis, in order to ensure that the above described latent factor exhibits measurement invariance across the covariates in this study, I tested for *configural* and *metric/scalar* measurement invariance using the Mplus 7.3 command: MODEL=CONFIGURAL, METRIC, SCALAR. *Configural* measurement invariance holds if the pattern of fixed and estimated parameters is equivalent across groups. In other words, *configural* invariance implies that the general structure of the model is appropriate for each subpopulation. *Metric* invariance implies that the factor loadings (slopes) are invariant, while *Scalar* invariance implies equality of both factor loadings (slopes) and intercepts (thresholds) across groups.

Given that my observed indicators are categorical, the thresholds and factor loadings (slopes) are related. Therefore, after testing for *configural* invariance, I compared the fit of the *configural* model to the *scalar* model across Gender, Minority Status, and First

Generation Status. Table 20 displays fit statistics for the *configural* and *scalar* models across the three covariates.

Table 20: CFA Measurement Invariance Model Comparisons.

Covariate	Model	Chi-Square	df	p-value	RMSEA	RMSEA CI	CFI	TLI
Gender	Configural Invariance:	6.176	4	0.186	0.017	(0.000 - 0.041)	0.998	0.995
	Scalar Invariance:	13.928	10	0.176	0.014	(0.000 - 0.030)	0.997	0.997
	Chi-Square difference test:	$\chi^2_{TRd} = 7.972, df = 6, p = .240$						
Minority Status	Configural Invariance:	2.866	4	0.580	0.000	(0.000 - 0.029)	1.000	1.003
	Scalar Invariance:	11.222	10	0.341	0.008	(0.000 - 0.026)	0.999	0.999
	Chi-Square difference test:	$\chi^2_{TRd} = 7.981, df = 6, p = .240$						
First Generation Status	Configural Invariance:	3.729	4	0.444	0.000	(0.000 - 0.033)	1.000	1.001
	Scalar Invariance:	10.746	10	0.378	0.012	(0.000 - 0.032)	0.999	0.998
	Chi-Square difference test:	$\chi^2_{TRd} = 6.885, df = 6, p = .332$						

Beginning with Gender, the adjusted chi-square difference test was not statistically significant (p > .05), indicating that the *configural* model fails to provide a significant increase in model fit compared to the *scalar* model. Moreover, the values of *RMSEA*, *CFI*, and *TLI* also indicate that the *scalar* model fits the data well. Similarly, with respect to both Minority Status and First Generation Status, the chi-square difference tests were not statistically significant (p = >.05), and the values of RMSEA, CFI, and TLI indicate that the *scalar* model has excellent model fit in each case.

Therefore, with respect to Gender, Minority Status, and First Generation Status, based on fit statistics reported in table 20, *scalar* measurement invariance can be assumed. Substantively, scalar measurement invariance implies that not only are the relationships between the factors and the indicators equivalent across groups, but also that two individuals with the same latent score, but from different subgroups, should have equal values on the indicators. Finally, given *scalar* measurement invariance, I can legitimately compare structural relationships and means across groups.

4.3: Latent Class Structural Models

Having established the two measurement models and assessed measurement invariance across the covariates, I now move to the structural latent class models using the three step approach described above. To begin, from the final latent class model with 4 classes and 6 direct effects, I recorded the *Logits for the Classification Probabilities for the Most Likely Latent Class Membership (Column)by Latent Class (Row)* from the Mplus 7.3 output. As mentioned in chapter 3, these logits express the average uncertainty with which cases were classified into their most likely latent class, based on maximum posterior class probability assignment.

In the third step, I instructed Mplus 7.3 to open a file exported from the first step, which includes each case and the most likely latent class, as well as any auxiliary variables I selected using the AUXILIARY command. As explained in chapter 3, I specified a new latent class model in which the nominal most likely class variables act as indicators of the latent class with measurement error pre-fixed at the rates calculated in step two (Asparouhov & Muthén, 2014b).

4.3.1: Model 1: Latent Class Regression

In line with my conceptual model, I first regress latent class membership on Gender, Minority Status and First Generation Status. A graphical depiction of Model 1 is displayed in Figure 4. Table 21 displays the logits, standard errors, logit/standard error, p-values and Odds Ratios (*OR*) odds associated with the multinomial regression of latent class on Gender, Minority Status, and First Generation College Status. The fourth latent class is designated as the reference class.

Figure 4. *Model 1: Latent Class Regression.*

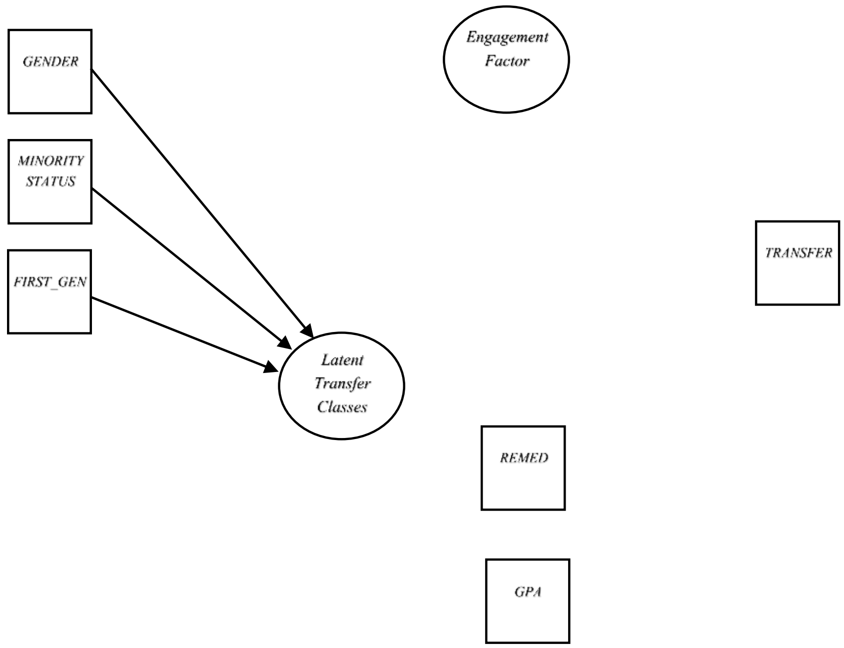


Table 21. Model 1 Latent Class Regression Coefficients.

Transfer Subtype	Covariate	*Logit*	*SE*	*Logit/SE*	*p Value*	*OR*
Class 1: High Transfer Intentions, Few Barriers	Female	0.006	0.187	0.310	0.98	1.006
	White/Asian	0.406	0.182	2.225	0.00*	1.500
	Not First-Generation	0.154	0.207	0.746	0.46	1.117
Class 2: Low Transfer Intentions, Some Barriers	Female	0.044	0.242	0.180	0.86	1.045
	White/Asian	0.736	0.249	2.952	0.00*	2.087
	Not First-Generation	-0.052	0.260	-0.200	0.84	0.949
Class 3: Moderate Transfer Intentions, Low Academic Resources	Female	-0.247	0.238	-1.038	0.30	0.781
	White/Asian	0.245	0.247	0.992	0.32	1.277
	Not First-Generation	-0.161	0.289	-0.556	0.58	0.851
Class 4: Moderate Transfer Intentions, Low Academic Momentum	Female					
	White/Asian			Reference Group		
	Not First-Generation					

**p* <.05.

First, based on the z-scores obtained from dividing the logits by their standard errors and controlling for all other covariates, only the logits associated with Minority status when comparing membership in Class 1 to Class 4, $z = 2.225$, $p = 0.026$ and Class 2 to Class 4, $z =$

2.952, p = 0.003 are statistically significantly different from zero (p< 0.05). More clearly, in terms of odds ratios, the odds of membership in Class 1 relative to Class 4 are 1.5 times greater for White/Asian students than for minority students (*OR=1.5*), and the odds of membership in Class 2 compared to class 4 are 2.087 times greater for White/Asian students than for minority students (*OR*=2.087). None of the other logits were statistically significantly different from zero (p<.05).

Globally, Table 22 displays four chi-square difference tests (*TRd*) comparing the null model without covariates to one with gender, minority status, first generation status each by itself, and a combined model with all three covariates. Moreover, *BIC* values associated with the null and candidate models are also provided. The results of in Table 22 are generally consistent with those reported in table 21. The only covariate that statistically significantly improved model fit, based on the chi-square difference test, was Minority Status, $\chi^2_{TRd} = 8.285, df = 3, p = 0.041$. However, the *BIC* value suggests that the null model fits the data slightly better than the one including Minority Status.

Table 22: Model 1: Latent Class Regression Model Fit Comparisons.

		LL	***df***	***BIC***
Gender	Model 1: Null Model	-4797.01	3	9618.86
	Model 2: Gender Only	-4794.75	6	9639.18
	$\chi^2_{TRd} = 2.17, df = 3, p = 0.548$			
Minority Status	Model 1: Null Model	-4797.01	3	9618.86
	Model 2: Minority Status Only	-4786.00	6	9621.67
	$\chi^2_{TRd} = 8.285, df = 3, p = 0.041$			
First Generation Status	Model 1: Null Model	-4797.01	3	9618.86
	Model 2: First Generation Status Only	-4792.40	6	9634.48
	$\chi^2_{TRd} = 3.769, df = 3, p = 0.288$			
Combined: Gender,	Model 1: Null Model	-4797.01	3	9618.86
Minority and First	Model 2: Combined Model	-4778.82	12	9656.98
Generation Status	$\chi^2_{TRd} = 14.745, df = 9, p = 0.098$			

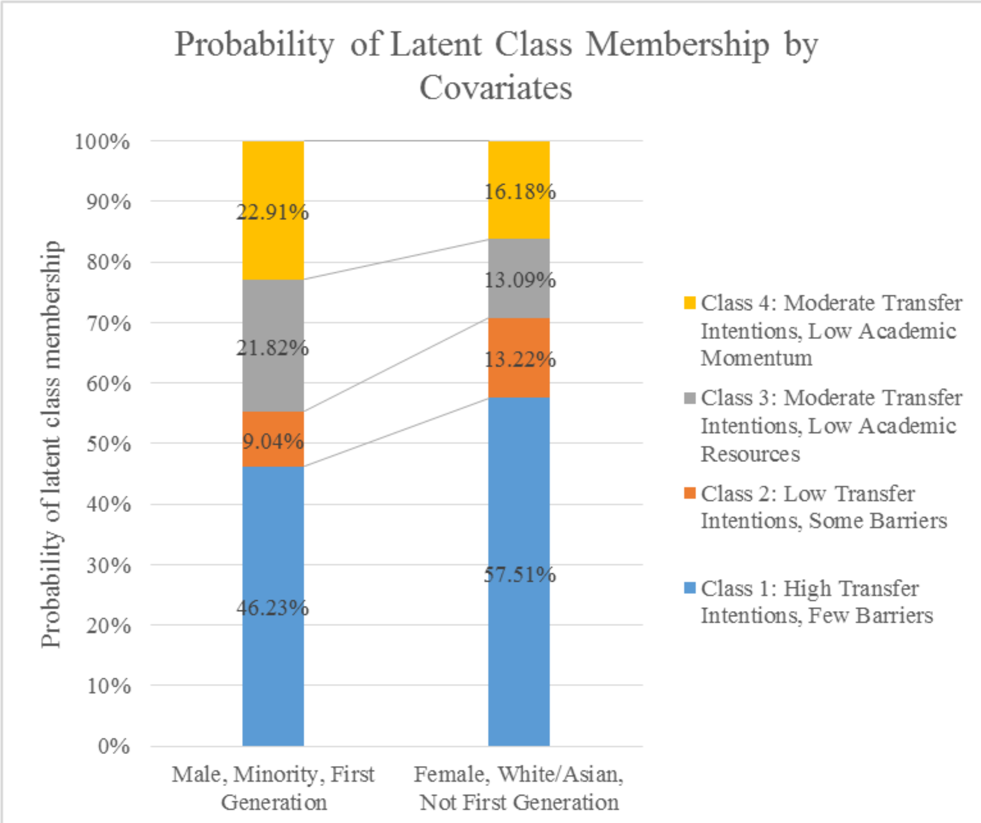
Although only minority status appears to statistically significantly predict latent class membership, I retain all three covariates as hypothesized in my conceptual model.

4.3.1.1: Model 1: Discussion of Latent Class Regression

To illustrate the effect of the covariates on latent class membership, I converted the odds ratios to probabilities summing to one. Figure 5 compares the estimated probabilities of latent class membership between students who were Male, Minority, and First Generation to students who were Female, White/Asian, and not First generation. From the transfer literature, students in the first group would be expected to have a lower likelihood of transferring to a four-year institution than those in the second group, based solely on these covariates.

Therefore, as convergent validity, I would expect that students in the second group would have higher probabilities of membership in *Latent Class 1: High Transfer Intentions, Few Barriers* than students in the higher risk group.

Figure 5: *Latent Class Probabilities by Covariates.*



As illustrated in Figure 5, Female, White/Asian, not first generation college students have an estimated probability of .575 of membership in latent Class 1. Conversely, the probability of latent class membership in latent Class 1 for male, minority, and first generation status is only .462. These differences are not large, but this makes sense given that the effects sizes (*OR*) of the covariates were small, and in most cases not statistically significant.

Further, with respect to classes 3 and 4, which are characterized by moderate transfer intentions and low academic resources in the first case, and low academic momentum in the second, the differences across the two groups of students in estimated probabilities of latent class membership also align with expectations; students in the first group, in general, are more likely both to arrive at community college with lower academic resources and delay postsecondary education than students in the second group.

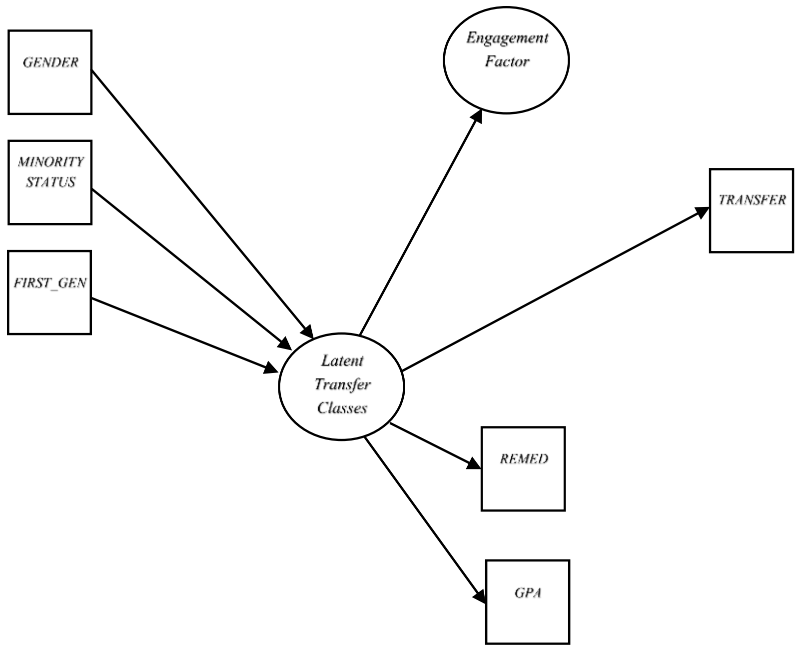
Finally, that students in the second group are more likely to be members of *Latent Class 2: Low Transfer Intentions, Some Barriers* than students in the first group was somewhat unexpected. However, some research suggests that students from some underrepresented minority groups have very high degree aspirations, along with lower academic resources, and high external demands (Dougherty & Kienzl, 2006). Therefore, it is possible that the latent model is reflecting this phenomenon.

Overall, though the covariates did not improve the fit of the unconditional latent class model, the associations among the covariates and expected latent class membership probabilities were generally in line with expectations, thus providing some degree of convergent validity. Conversely, that the latent classes are not simply proxies for the covariates, as evidenced by the weak associations between the covariates and latent class membership, provides some degree of divergent validity.

4.3.2: Model 2: Distal Outcomes

Conditional on the above mentioned covariates, the second model examines the effect of latent class membership on four distal outcomes: Transfer, Remediation, GPA, and Academic Engagement. Figure 6 provides a graphic representation of Model 2.

Figure 6. *Model 2: Distal Outcomes.*



Before proceeding to the final models hypothesized in my conceptual model, I first examine the distal outcomes without additional paths in order both to assess the predictive validity of the latent class model and to examine whether there are any observed or latent variables for which predicted item response probabilities do not vary within a given class.

Table 23 displays the conditional item response probabilities for each distal outcome across each latent class. Moreover, Table 23 also includes estimates, standard errors, z-scores, and associated p-values for each pairwise comparison of latent class with respect to each distal outcome.

Table 23: Model 2: Distal Outcomes by Latent Class Membership.

Probability of Transfer by Latent Class	Prob	Class Comparisons	Estimate	SE	Estimate/SE	p Value
Class 1: High Transfer Intentions, Few Barriers	0.438	Class 1 - 4	-1.373	0.310	-4.431	0.00*
Class 2: Low Transfer Intentions, Some Barriers	0.019	Class 2 - 1	3.700	0.965	3.834	0.00*
Class 3: Moderate Transfer Intentions, Low Academic Resources	0.236	Class 2 - 4	2.327	1.033	2.252	0.02*
Class 4: Moderate Transfer Intentions, Low Academic Momentum	0.165	Class 3 - 1	0.925	0.165	5.618	0.00*
		Class 3 - 2	-2.774	0.976	-2.841	0.00*
		Class 3 - 4	-0.447	0.355	-1.258	0.21

Probability of Remediation by Latent Class	Prob	Class Comparisons	Estimate	SE	Estimate/SE	p Value
Class 1: High Transfer Intentions, Few Barriers	0.352	Class 1 - 4	0.289	0.197	1.469	0.14
Class 2: Low Transfer Intentions, Some Barriers	0.327	Class 2 - 1	-0.037	0.206	-0.178	0.86
Class 3: Moderate Transfer Intentions, Low Academic Resources	0.335	Class 2 - 4	0.252	0.285	0.884	0.38
Class 4: Moderate Transfer Intentions, Low Academic Momentum	0.274	Class 3 - 1	0.076	0.171	0.446	0.66
		Class 3 - 2	0.113	0.244	0.462	0.64
		Class 3 - 4	0.365	0.257	1.418	0.16

Mean Academic Engagement by Latent Class	Mean	Class Comparisons	Estimate	SE	Estimate/SE	p Value
Class 1: High Transfer Intentions, Few Barriers	0.870	Class 1 - 4	0.870	0.170	5.132	0.00*
Class 2: Low Transfer Intentions, Some Barriers	0.140	Class 2 - 1	-0.730	0.119	-6.141	0.00*
Class 3: Moderate Transfer Intentions, Low Academic Resources	0.600	Class 2 - 4	0.140	0.198	0.707	0.48
Class 4: Moderate Transfer Intentions, Low Academic Momentum	0.000	Class 3 - 1	-0.270	0.139	-1.940	0.05*
		Class 3 - 2	0.460	0.170	2.702	0.01*
		Class 3 - 4	0.600	0.208	2.891	0.00*

Mean Grade Point Average (G.P.A) by Latent Class	Mean	Class Comparisons	Estimate	SE	Estimate/SE	p Value
Class 1: High Transfer Intentions, Few Barriers	2.835	Class 1 - 4	0.119	0.084	1.415	0.16
Class 2: Low Transfer Intentions, Some Barriers	2.773	Class 2 - 1	-0.062	0.075	-0.825	0.41
Class 3: Moderate Transfer Intentions, Low Academic Resources	2.623	Class 2 - 4	0.058	0.107	0.540	0.59
Class 4: Moderate Transfer Intentions, Low Academic Momentum	2.716	Class 3 - 1	-0.212	0.077	-2.769	0.01*
		Class 3 - 2	-0.151	0.109	-1.386	0.17
		Class 3 - 4	-0.093	0.120	-0.775	0.44

*p <.05.

Beginning with the fundamental dependent variable, Transfer, the estimated probability of transferring to a four-year institution, given membership in *Class 1: High Transfer Intentions, Few Barriers*, was .438, compared to .019 for students in latent *Class 2: Low Transfer Intentions, some barriers*. This difference was statistically significant, z = 3.834, $p < .05$, and in the expected direction. Moreover, students in *Class 2: Low Transfer Intentions, some barriers*, had nearly zero probability of transfer, which has implications for subsequent model parameterization. Lastly, the estimated probabilities for classes 3 and 4 were not statistically significantly different from each other $z = -1.258$, $p > .05$, yet both were statistically significantly different from classes 1 and 2.

Turning to remediation, as illustrated in table x, the estimated item response probabilities range from .274 in *Class 4:Moderate Transfer Intentions, Low Academic Momentum* to 0.352 in *Class 1:High Transfer Intentions, Few barriers* class. However, none of the differences in remediation probabilities across any of the class combinations was statistically significant (p<.05).

Interestingly, the greatest estimated probability of remediation was found in *Class 1: High Transfer Intentions, Few barriers,* where students have the highest academic resources among the latent classes. If remediation were a signal of low academic resources, then I would have expected that students in *Class 3: Moderate Transfer Intentions, Low Academic Resources* would have had the greatest probability of remediation. Given this is not the case, it is unclear what specific mechanism drives remediation likelihoods.

With respect to the Academic Engagement latent factor means, first, for identification purposes, the factor mean was set to zero in class 4 and estimated freely across the other three classes, with fixed interclass variances. Though the actual scale of the factor scores is substantively unimportant, the relative magnitude of the scale is. The estimated Academic Engagement mean factor score was greatest in *Class 1: High Transfer Intentions, Few barriers* (.870) and lowest in *Class 4: Moderate Transfer Intentions, Low Academic Momentum* (0.00). The Class 1 estimated engagement factor mean was statistically significantly different from both Class 2, z = -6.141, p < .05 and class 4, z = 5.132, p < .05.

The fourth class, *Moderate Transfer Intentions, Low Academic Momentum* had the lowest mean engagement score among the classes—factor mean set to zero.

This finding makes sense given that enrollment intensity is correlated with engagement. More precisely, students enrolled less than full-time are more likely to have lower levels of engagement than full-time students (Quaye & Harper, 2014).

Finally, the last distal outcome examined across latent classes is mean first-year Grade Point Average (GPA). As expected, students in *Class 1: High Transfer Intentions, Few barriers*, had the highest mean first-year community college GPA (2.85), while *Class 3: Moderate Transfer Intentions, Low Academic Resources,* had the lowest (2.623); this difference was also statistically significant, $z = -2.769$, $p < .05$. Unlike in the case of remediation, students in *Class 3: Moderate Transfer Intentions, Low Academic Resources,* who arrive to college with the lowest academic resources among the classes, also had the lowest first-year college GPA, and, conversely, as expected, students in *Class 1: High Transfer Intentions, Few barriers* had the highest first-year college GPA.

4.3.2.1: Discussion of Model 2

The second research question this dissertation attempts to address is, conditional on relevant student demographics, what is the relationship between latent class membership and likelihood of transfer? In this section, I assessed the effects of latent class membership on the likelihood of transfer, remediation, student engagement, and first year GPA. With respect to transfer, the dependent variable of most interest in this study, the latent class model demonstrates acceptable criterion validity, given that estimated probabilities of transfer vary across classes as expected, particularly between latent *Class 1: High Transfer Intentions, Few barriers,* and *Class 2: Low Transfer Intentions, Some barriers*. With respect to Class 2, the probability of transfer is essential zero.

Similarly, both Academic Engagement and first-year GPA vary across latent classes in expected ways. That is, students in the latent class with lowest academic momentum were least engaged; likewise, students in the latent class with lowest academic resources were also most likely to have lower college GPAs, and vice versa. However, the latent class model was unable to predict remediation patterns with any degree of certainty. What's more, the statistically insignificant differences that were observed, failed to align with intuition. For example, students in *Class 1: High Transfer Intentions, Few barriers* were most likely to have enrolled in at least one remedial course during their first year of community college.

Overall, with the exception of remediation, the associations between latent class membership and the distal outcomes provide additional support for the construct validity of the model. As mentioned in my introduction, the reason I chose to conduct a latent class analysis was not to merely predict transfer directly, but rather, first, to arrive at a manageable number of substantively different subgroups on the basis of their transfer intentions and academic risk factors, and, second, test whether the effects of malleable research based variables might vary across latent classes. Finally, if there were differential treatment effects across latent classes, community colleges could then use such information to construct latent class specific treatments. Latent class specific treatments could represent a compromise between one-size fits all and individualized strategies to increase the number of students who do transfer.

4.5: Final Structural Models:

In Model 1, I regressed latent class membership on Gender, Minority Status and First Generation Status. In Model 2, conditional latent class membership predicted four distal outcomes: Transfer, First-Year GPA, Remediation, and the latent Engagement factor. Model 2 served as an intermediary model that sought to both establish some degree of criterion validity and examine intraclass variability in the distal outcomes. Model 3 regressed Transfer on observed variables Gender, Minority Status, First Generation Status, GPA, Remediation, and the latent Engagement factor. Model 3 could be referred to as a class-specific intercept model as the intercepts vary by latent class. Finally, Model 4 differs from Model 3 in that latent class membership now moderates the relationships between Gender, Minority Status, First Generation Status, first-year GPA, Remediation, Engagement and Transfer. Model 4 could be referred to as a class-specific-intercept and class-specific slope model given that both the intercepts and slopes are allowed to vary across latent classes.

Substantively, Model 3 assumes that the associations between the covariates and transfer are the same across latent classes, but the intercepts, or the estimated probability of transfer when all covariates are equal to zero, vary across classes; Model 4 assumes that not only the intercepts, but the relationships between the covariates and transfer vary across latent classes.

4.5.1: Model 3: Class Specific Intercepts

Model 3 is displayed graphically in Figure 7:

Figure 7. *Model 3: Class-Specific Intercepts.*

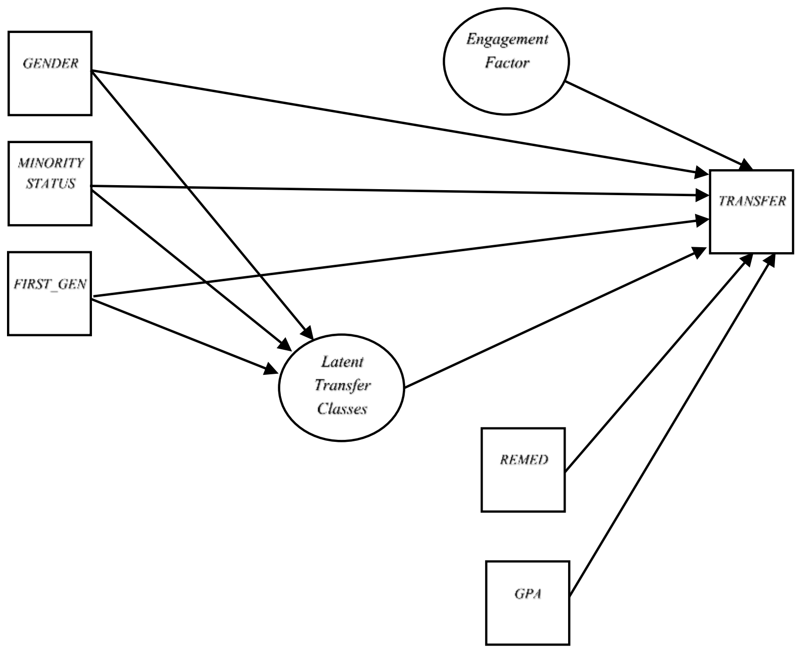


Table 24 displays the parameter estimates for the logistic regression of transfer on the selected covariates by latent class for both models. Beginning with Model 3, as mentioned above, only the intercepts vary across latent class, therefore the slope estimates are identical across classes. First, with respect to the intercepts in Model 3, latent *Class 1: High Transfer Intentions*, *Few barriers* has the smallest estimated threshold, which means that, when all covariates are equal to zero, students in latent Class 1, have the highest probability of transferring among the four latent classes. Specifically, given membership in latent Class 1, students who are male, minority, first generation, remediated and had an average GPA (grand mean centered), and an estimated engagement factor score of zero, the probability of transferring to a four-year institution is .22. By comparison, students with the same characteristics, but who are in latent Class 3, have an estimated probability of transferring of only .13; likewise for latent class 4, the probability of transfer is .09. Finally, the estimated probability of transfer for students in latent Class 2, when all covariates are set to zero, is less than .01.

With respect to the slope estimates in Model 3, beginning with the student background characteristics, only First-Generation College status resulted in a statistically significant change in the log odds of transfer, $z = 5.27$, $p < .05$. Substantively, on average and controlling for all the other covariates in the model, the odds of transferring are 1.78 times greater for students who are not first-generation than for students who are first generation, regardless of latent class membership.

Table 24: Models 3 and 4: Class Specific-Intercepts and Slope Estimates.

		MODEL 3: Class-Specific Intercepts					MODEL 4: Class Specific Intercepts and Slopes				
		Estimate	*S.E.*	*Est./S.E.*	*p-value*	*OR*	*Estimate*	*S.E.*	*Est./S.E.*	*p-value*	*OR*
Class 1: High Transfer Intentions, Few Barriers	β_{01}	1.26	0.18	7.17	0.00*		1.43	0.21	6.75	0.00*	
	β_1's										
	Female	0.04	0.11	0.37	0.71	1.04	0.09	0.15	0.63	0.53	1.10
	White/Asian	0.16	0.12	1.37	0.17	1.18	0.19	0.15	1.29	0.20	1.21
	Not First Gen	0.58	0.11	5.27	0.00*	1.78	0.47	0.16	3.04	0.00*	1.60
	Not Remediated	0.58	0.10	5.75	0.00*	1.79	0.76	0.13	5.76	0.00*	2.13
	GPA	0.55	0.09	6.21	0.00*	1.73	0.68	0.10	7.13	0.00*	1.98
	Engagement	0.25	0.07	3.82	0.00*	1.28	0.27	0.08	3.24	0.00*	1.31
Class 2: Low Transfer Intentions, Some Barriers	β_{02}	5.07	1.18	4.30	0.00*		3.77	0.70	5.36	0.00*	
	β_1's										
	Female	0.04	0.11	0.37	0.71	1.04	Not Estimated due to lack of variance in Transfer Outcome				
	White/Asian	0.16	0.12	1.37	0.17	1.18					
	Not First Gen	0.58	0.11	5.27	0.00*	1.78					
	Not Remediated	0.58	0.10	5.75	0.00*	1.79					
	GPA	0.55	0.09	6.21	0.00*	1.73					
	Engagement	0.25	0.07	3.82	0.00*	1.28					
Class 3: Moderate Transfer Intentions, Low Academic Resources	β_{03}	1.99	0.22	9.10	0.00*		1.59	0.46	3.45	0.00*	
	β_1's										
	Female	0.04	0.11	0.37	0.71	1.04	0.11	0.29	0.36	0.72	1.11
	White/Asian	0.16	0.12	1.37	0.17	1.18	0.02	0.31	0.05	0.96	1.02
	Not First Gen	0.58	0.11	5.27	0.00*	1.78	0.64	0.28	2.31	0.02*	1.90
	Not Remediated	0.58	0.10	5.75	0.00*	1.79	0.19	0.37	0.50	0.62	1.21
	GPA	0.55	0.09	6.21	0.00*	1.73	0.28	0.18	1.58	0.11	1.32
	Engagement	0.25	0.07	3.82	0.00*	1.28	0.10	0.14	0.70	0.48	1.10
Class 4: Moderate Transfer Intentions, Low Academic Momentum	β_{04}	2.38	0.31	7.68	0.00*		2.14	0.53	4.07	0.00*	
	β_1's										
	Female	0.04	0.11	0.37	0.71	1.04	-0.35	0.35	-1.01	0.31	0.70
	White/Asian	0.16	0.12	1.37	0.17	1.18	0.19	0.38	0.51	0.61	1.21
	Not First Gen	0.58	0.11	5.27	0.00*	1.78	0.99	0.46	2.15	0.03*	2.69
	Not Remediated	0.58	0.10	5.75	0.00*	1.79	0.33	0.52	0.64	0.52	1.40
	GPA	0.55	0.09	6.21	0.00*	1.73	0.35	0.32	1.09	0.27	1.42
	Engagement	0.25	0.07	3.82	0.00*	1.28	0.34	0.19	1.80	0.07	1.41

*p <.05.

Continuing with Model 3, considering the student experience and academic performance variables, all three variables resulted in statistically significant changes in the log odds of transfer (p<.05). As displayed in table 24, the odds of transfer for students who did not take a remedial class during their first year were 1.79 times the odds for students who did take a remedial course. Similarly, an increase of one grade point above the average GPA for the sample, increased the odds of transfer by 1.73 times. Finally, the odds of transfer associated with a one unit increase above zero (the factor score for the reference group: latent Class 2) in the estimated latent engagement score increased the odds of transfer by 1.28 times.

4.5.1.1: Discussion of Model 3: Class-Specific Intercepts

The conceptual model portrayed in Figure 7 posited that student background variables influence latent class membership, which in turn influence distal outcomes. However, the results of Model 1: Latent Class Regression indicated that only Minority Status statistically significantly predicted latent class membership. Moreover, globally, the results of the chi-square difference test indicated that the unconditional latent class model fit the data better than the model that included the covariates. With respect to Model 3, neither Minority status nor Gender was statistically significantly related to Transfer, when controlling for latent class and the other independent variables. This result replicated the findings of several community college transfer studies (Dougherty & Kienzl, 2006; Horn, 2009; Roksa, 2006).

Nevertheless, First-Generation College status, while not a significant predictor of latent class membership, was a strong predictor of Transfer (*OR*=1.783). Due to limitations in the dataset, neither a composite measure of Socioeconomic Status nor all of the typical components (i.e., income, occupational prestige, etc.) were available. While imperfect, First-Generation college status served as a proxy for socioeconomic status in this study. Unfortunately, my results replicate the findings of Dougherty and Kienzl (2006) who found that, despite controlling for other student demographic background variables, academic resources, external demands, academic momentum, and college experiences and performance, first generation status remained a strong predictor of four-year transfer.

With respect to Remediation, the results from Model 3 indicate that, once again, controlling for all of the aforementioned variables, students who were not exposed to remediation in their first year of community college, were significantly more likely to transfer (OR=1.793). This finding supports an ever-growing research literature questioning the value of remedial education (Jones, 2012; Rose, 2011).

Turning to student academic performance, as expected, student grade point average in the first year of community college was statistically significantly related to transfer. For example, an increase of 1 grade point (e.g., from a 2.0 gpa to a 3.0 gpa) resulted in a 73% increase in the odds of transfer.

Finally, model 3 showed that student engagement was statistically significantly related to transfer. This finding was significant, given that most studies of community college outcomes, which control for the variables included in this model, have failed to find a statistically significant relationship between student engagement and transfer. As hypothesized in chapter 3, the fact that I modeled engagement as a measurement error corrected latent factor, may have contributed to the significant result. Nevertheless, while the engagement slope was statistically significant, the effect size was low, given that a one unit increase is equal to one standard deviation of change in the latent factor.

In addition to the above mentioned statistically significant slope parameters, the latent class model allows the intercepts to vary by class. In other words, the differences in the intercepts reflect the differences in the probability of transfer across the latent classes, when all the covariates are set to zero. Because the likelihood of transfer varies by latent class, as exhibited in model 2, the changes in the log odds of transfer, though equivalent across classes in model 3, lead to different model predicted probabilities of transfer. For example, the model estimated probabilities of transfer, when all binary covariates are equal to one and both GPA and Engagement are increased by 1 unit, range from .05 in latent

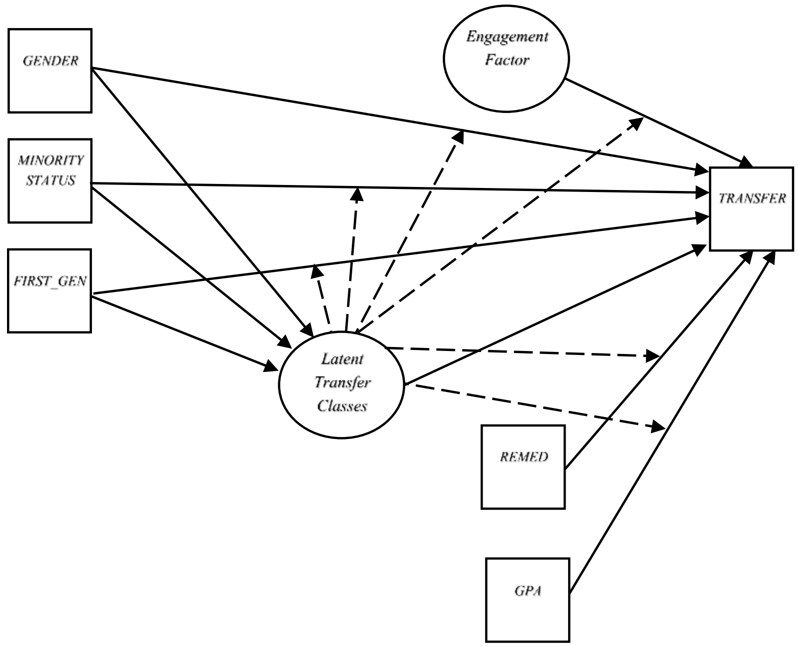
Class 2: *Low Transfer Intentions, some barriers* to .71 in latent Class 1: *High Transfer Intentions*, *Few barriers*.

This result highlights one of the potential benefits associated with using a latent class approach to examine a complex array of covariates. Namely, given the more than 600 observed response patterns across the 8 latent class indicators, the latent class model was able to classify students into four meaningful, measurement error-corrected latent classes, which are relatively distinct and large enough to allow class-specific modelling. The results from such class specific modeling may enable underfunded community colleges to strategically address the charge to increase transfer rates.

4.5.2: Model 4: Class Specific Intercepts and Slopes

Model 4 extends Model 3 by allowing not only the intercepts to vary across classes, but also the slopes. Displayed in Figure 8, Model 4 represents an example of latent class moderation wherein the relationships among the covariates and transfer depend upon latent class. The dotted lines from the latent class to the various paths imply that the relationships between the variables and Transfer are moderated by latent class membership.

Figure 8. *Model 4: Class-Specific Slopes.*



As displayed in table 24, Model 4, beginning with latent *Class 1: High Transfer Intentions, Few barriers*, the results are generally similar, with respect to the direction and statistical significance of the slopes, but the magnitudes of the slopes, and thus the effect sizes are quite different from Model 3. Moreover, the Model 4 class-specific intercept in latent Class 1 is larger than in Model 3, which implies that zero values on all of the covariates in Model 4 results in a lower probability of transfer than was estimated in Model 3 with the same covariate values. However, the slope estimates in Model 4, latent Class 1, and thus the odds ratios associated with Remediation, GPA and Engagement were greater in Model 4 than in Model 3, while the effect of First Generation Status decreased between Model 3 and 4.

Conversely, in classes 3 and 4, only the change in log odds of transfer associated with not being a First Generation student were statistically significant (p <. 05). However, in Model 4 and latent class 4, the slope of the engagement factor increased from Model 3 and was statistically significant at an alpha of .10, (*p* =.07). This result is interesting given that students in latent class 4: *Moderate Transfer Intentions, Low Academic Momentum* were most likely to have delayed entry after high school and least likely to be enrolled full-time. Specifically, given that part-time students are typically the least engaged, this result suggests that students who do manage to increase engagement, despite their limited exposure to campus, might experience higher probabilities of transfer.

From an overall comparison of model fit between model 3 and 4, the preponderance of non-significant slope coefficients in Class 3 and 4 are also reflected in results of the chi-square difference test displayed in Table 25.

Table 25: Model Fit Comparison: Models 3 and 4.

	LL	***df***	***BIC***
Model 3: Class Specific Intercepts	-19772.255	37	39850.83
Model 4: Class Specific Intercepts and Slopes	-19759.714	49	39925.10
$\chi^2_{TRd} = 12.81, df = 12, p = 0.383$			

The Latent Class Moderation Model (4) does not result in a statistically significant improvement in model fit compared to Model (3). $\chi^2_{TRd} = 12.81, df = 12, p > .05$.

4.5.2.1: Discussion of Model 4

It is possible that the class-specific intercept and slope Model results in insufficient power to detect the rather small effect sizes across classes. That is to say, given that the sample size is reduced within each latent class, as well as the number of transfer events in those classes where transfer is less probable, the class specific logistic regressions in classes 3 and 4 may not have enough power to detect the effects of the covariates on the likelihood of transfer.

Based on the work of Vittinghoff and McCulloch (2007), who conclude on the basis of simulation studies that 10 events per covariate is sufficient to achieve power of .80, it would appear that I do have sufficient power in each of the latent classes except Latent Class 2, the parameters of which are not estimated. Specifically, given this guideline of 10 events per covariate, Class 1 could achieve sufficient power with as many as 89 covariates, whereas Class 3 and 4 could accommodate 18 and 12 covariates respectively. Nevertheless, Hosmer Jr, Lemeshow, and Sturdivant (2013), while generally supportive of the 10 events per covariate rule, are less convinced of its reliability in cases where the distribution of binary covariates are not evenly distributed. This appears to be an area for future research.

What is clear when comparing Models 3 and 4 is the significant impact Class 1 has on the Model 3 estimates of the other latent classes. Notwithstanding the lack of statistical significance in the slope estimates in Model 4, it is evident in general that the class specific slopes for latent classes 3 and 4 are generally weaker, with the exception of first generation status, than the Class 1 influenced slopes estimated in Model 3. While the overall fit of Model 3 is better than Model 4, it is clear from Model 4 that the relationships among the student experience and performance variables and transfer vary across classes. This is evidenced by the lack of statistical significance of these slope parameters in classes 3 and 4 in Model 4. However, a formal statistical test of the differences in regression coefficients across classes in model 4 reveals that only one regression coefficient, GPA, is statistically significantly different across two classes; specifically, the GPA slope for Class 3 is statistically significantly lower than the GPA slope for Class 1, $z = -1.974$, $p<.05$.

Finally, based on the work of McKelvey and Zavoina (1975), Mplus 7.3 provides R-Square values for binary outcomes based on the y* assumption discussed in chapter 3. Table 26 displays the class-specific proportions of variance explained in transfer outcome by the selected covariates across Models 3 and 4.

Table 26. R-Square Values for Models 3 and 4.

	MODEL 3: Class Specific Intercepts				MODEL 4: Class Specific Slopes			
Latent Class	*Estimate*	*S.E.*	*Est./S.E.*	*P-Value*	*Estimate*	*S.E.*	*Est./S.E.*	*P-Value*
Class 1: High Transfer Intentions, Few Barriers	0.13	0.02	6.80	0.00*	0.17	0.03	5.70	0.00*
Class 2: Low Transfer Intentions, Some Barriers	0.13	0.02	6.71	0.00*	Not Estimated			
Class 3: Moderate Transfer Intentions, Low Academic Resources	0.13	0.02	6.74	0.00*	0.05	0.03	1.65	0.10
Class 4: Moderate Transfer Intentions, Low Academic Momentum	0.13	0.02	6.65	0.00*	0.15	0.07	2.14	0.03*

*p <.05.

As is evident, the R-Square values from Model 3 are essentially equivalent across latent classes since only the intercepts vary across classes. By contrast, the values of R-square for Model 4, where both the intercepts and slopes vary across classes, are quite variable, especially between classes 1 and 3 and 3 and 4. Effectively, with respect to Class 3, the covariates fail to explain a statistically significant proportion of variance in transfer likelihood (R^2 =.05, p > .05). Conversely, R-square values for both latent classes 1 and 4 in Model 4 are increased compared to Model 3 and are statistical significant (p < .05). This result further elucidates the strong impact Class 1 has on the overall results when slopes are constrained to be equal across classes. Based on R-square values, Model 4, compared to Model 3, explains more of the variance in transfer for students in classes 1 and 4, but explains significantly less variance in transfer outcomes than Model 3 for students in Class 3.

Finally, while the R-square values are small, they actually represent the incremental validity associated with the covariates over and beyond that explained by the latent classes.

For example, in Model 4, Class 1, after controlling for the latent class, the covariates explain an additional 17% of the variance in transfer outcomes.

4.6: Discussion of Models 1 thru 4

The first part of this study involved conducting an unconditional latent class analysis. The chosen manifest items represented four literature supported domains associated with transfer outcomes: (i) Academic Resources, (ii) Transfer intentions, (iii) External Demands, and (iv) Academic Momentum. Based on an analysis of several model fit indices, and substantive interpretability, the four class model emerged as the best fitting and most interpretable of the candidate models.

While there was variation in the measurement quality of the indicators, overall they provided adequate homogeneity and latent class separation, as well as interpretable classes. Moreover, the classification quality of the latent class model, based on several global and class specific classification measures, was moderate to high both overall and across latent classes. Accordingly, based on the patterns of item response probabilities across the classes, I assigned names to each class reflective of the substantive differences in item response patterns: *Class 1: High Transfer Intentions, Few Barriers*, *Class 2: Low Transfer Intentions, Some Barriers*, *Class 3: Moderate Transfer Intentions, Low Academic Resources*, *Class 4: Moderate Transfer Intentions, Low Academic Momentum.*

Next, latent class measurement invariance was assessed across Gender, Minority Status, and First Generation College Status. Configural invariance was established by confirming that the 4 class model best fit the data within each subgroup. Metric/Scalar invariance was established by comparing the fit between models where the conditional item response variables were constrained to be equal across groups to models where they were freely estimated. Though some of the chi-square difference tests disagreed with the information criteria, the preponderance of the evidence suggested that metric/scalar invariance could be assumed.

Because the structural models use the three-step procedure in which the reliability of the indicators is fixed in the third step, it was important to test for direct effects from covariates to indicators, given that simulation studies suggest that omitting such direct effects may lead to biased estimates in the final structural models (Asparouhov & Muthén, 2014a).

There were six statistically significant direct effects from covariates to indicators. The inclusion of these direct effects resulted in a significant reduction in the information criteria, particularly with respect to *aBIC*. Prior to including these direct effects, *aBIC* failed to decrease even when 7 classes were extracted, but when these direct effects were added, *aBIC* agreed with the other information criteria. This finding corroborated the results of simulation studies conducted by Swanson et al. (2012), which indicated that, in the face of local dependence with sample sizes of 2000, *aBIC* overestimated the number of classes 100% of the time.

After establishing the latent class measurement model, a confirmatory factor analysis was performed to measure the hypothesized latent factor that I refer to as engagement. The overall model showed excellent model fit and each of the indicators had high factor loadings. Moreover, the latent factor model possessed configural and metric/scalar measurement invariance across the aforementioned subgroups

The second part of this study tested four structural models using the three step procedure. Fixing the nominal most likely class indicators to the values of the misclassification logits obtained from the latent class model with direct effects, the first model regressed latent class membership on Gender, Minority Status, and First Generation Status. Only Minority Status statistically significantly predicted latent class membership.

Model 2 examined the associations between latent class membership and four distal outcomes, including Transfer. There was significant variation in the proportions and means of each of the distal outcomes, except for remediation, across the latent classes. For example, estimated transfer probabilities varied from .02 in *Class 2: Low Transfer Intentions, Some Barriers*, to .43 in *Class 1: High Transfer Intentions, Few Barriers.* Variation among classes with respect to GPA and Engagement were as expected, providing further evidence, in the form of criterion validity, to support the construct validity of the transfer latent class model. As an aside, remediation levels did not vary across classes, despite significant variation in academic resources across latent classes.

Model 3 regressed Transfer on the student background variables and the student experience/academic performance variables. In this model, the intercepts varied across classes, but the relationships between the covariates and transfer were constrained to be equal across classes. The results showed that only First Generation status, among the student background variables, and all three of the student experience/academic performance variables statistically significantly predicted transfer likelihood. Not having taken a remedial course, not being first generation, and having a first-year GPA one unit above the sample average all had similarly moderate effect sizes with odds ratios near 1.7.

Although slopes were equivalent in Model 3, that the intercepts varied across classes led to different model predicted probabilities of transfer across classes. In other words, the class-specific intercepts captured the differences in class specific probability of transfer when the covariates were set to zero. As a result, latent classes in which the probability of transfer was high to begin with, had higher predicted probabilities based on the values of the covariates than a latent class starting with a lower unconditional transfer probability.

Finally, Model 4 allowed the intercepts and slopes to vary across classes. Though the fit for Model 4 was worse than Model 3, and only one slope was statistically significantly different across at least two classes, Model 4 did facilitate a class-specific view of the differential effects of the covariates. For example, in Model 4, within *Class 1: High Transfer Intentions, Few Barriers*, all the slopes in Model 3 were still statistically significant in Model 4, but the magnitude of many of the slopes had changed. For example, the regression coefficients associated with not having been remediated and a unit increase in GPA increased substantially in Model 4 compared to Model 3. Moreover, in Model 4, for classes 3 and 4, only the coefficients associated First Generation are statistically significant, and, the magnitude of its effect has increased.

In sum, model 4 suggests that Remediation, GPA, and Engagement are important factors for students in Class 1, but that these factors do not statistically significantly predict transfer for students in classes 3 and 4. Rather, for classes 3 and 4, first generation status is the best predictor of transfer likelihood. And, interestingly, with respect to class 4 in which students have low academic momentum, engagement is predictive of transfer (p <.10). This suggests that increasing engagement for students, who are more likely to have delayed entry and are enrolled part-time, may ameliorate some of the deleterious effects of low academic momentum on the probability of transfer. Finally, *Class 2: Low Transfer Intentions, Some Barriers* effectively describes a transfer subtype that does not transfer. Therefore, an examination of the effects of other covariates on transfer likelihood in Class 2 was irrelevant.

CHAPTER 5: CONCLUSIONS

With nearly half of all postsecondary students beginning at community colleges, and more than 80% of these students expecting to earn at least a bachelor's degree, that only roughly 27% eventually transfer to four-year institutions calls into question whether community colleges actually do provide a viable path toward a bachelor's degree (Long & Kurlaender, 2009). Moreover, such low transfer rates disproportionately affect the most disenfranchised of students, who are both more likely to attend community colleges and less likely to transfer to four-year institutions. Yet for community college students who do transfer to four-year institutions, their odds of baccalaureate degree completion are on par with similar native four-year students (Monaghan & Attewell, 2014). As is well established, students who complete bachelor's degrees reap lifetime financial, health, and social benefits that far surpass those of students who do not (Oreopoulos & Petronijevic, 2013; Reynolds & Ross, 1998; Taylor, Fry, & Oates, 2014). Therefore, given the profile of students who attend community colleges, the high graduation rates among community college students who do transfer, and the well-documented gains associated with baccalaureate completion, improving community college transfer rates to four-year institutions is one powerful means of addressing social and economic inequality in the United States.

Hence, the goals of this dissertation were, first, to identify and better understand malleable factors that influence community college transfer, and, second, to determine if the relationships between these factors and transfer were the same across different hypothesized latent transfer subtypes. The constructs and general conceptual model for this study drew upon earlier models of community college transfer proposed and tested by (Dougherty & Kienzl, 2006); Lee and Frank (1990); Nora and Rendon (1990); Wang (2012), etc. However, unlike prior studies, this dissertation tested whether a population of beginning community college students could be classified into a small number of homogenous groups, each reflecting a meaningful transfer subtype characterized by varying degrees of academic resources, transfer intentions, external demands, and academic momentum. As discussed in Chapter 3 and 4, a latent class measurement model was used to identify the hypothesized latent transfer subtypes. More precisely, from the more than 650 observed response patterns, four meaningful measurement error-corrected transfer subtypes were identified. Based on an examination of several different fit indices and measures of classification quality, the final model was not only substantively interpretable, but supported statistically.

An increasing number of recent studies have used latent class analysis to classify individuals into meaningful classes (Cavrini, Galimberti, & Soffritti, 2009; Lanza & Rhoades, 2013; Nylund, Bellmore, Nishina, & Graham, 2007; Yuan et al., 2014). Although the ability to classify individuals into meaningful subtypes is useful on its own, my impetus for doing so was to examine differential treatment effects or relationships across different transfer subtypes. A motivating example was conducted by Cooper and Lanza (2014), who used latent class analysis to identify risk subtypes among children who received the "treatment" of the federally funded Head Start preschool program or were assigned to the control group (untreated). After classifying children into one of five risk subtypes, the authors assessed whether the effects of Head Start on several distal outcomes were the same for children in different risk subtypes. The results revealed that Head Start participation was associated with positive outcomes for members of some risk subtypes, neutral outcomes for others, and negative outcomes for still other risk subtypes.

Returning to the present study, the latent transfer subtypes were measured by several observed indicators that have been shown to influence transfer. Although some of these indicators represent potentially malleable factors, it would be difficult to change most of them at the point when the community college student arrives at the counseling office on the first day of school. For example, it would be next to impossible to change students' academic resources accrued in high school, delay status, or level of financial dependency. It is, I suppose, conceivable that students could decide to work less, enroll full-time or increase their transfer intentions, but these factors are interrelated and unlikely alterable at the time of enrollment.

Therefore, latent transfer subtypes, though not as immutable as student background characteristics, are assumed to be fixed at the point when the student walks on the community college campus. Several studies have demonstrated the relationships between the observed latent class indicators I used and transfer. Not surprisingly, the results of my analysis showed that *Class 1: High Transfer Intentions, Few Barriers,* which is characterized by students with high academic resources, high transfer intentions, low external demands and high academic momentum had the highest probability of four-year transfer (.43). This result replicates the findings of several transfer studies (Dougherty & Kienzl, 2006; Lee & Frank, 1990; Wang, 2012). Moreover, the results of my study also corroborate the unsettling finding by Dougherty and Kienzl (2006) that, conditional on latent class membership, Gender and Race/Ethnicity, first-generation college students (my proxy for SES) were significantly less likely to transfer.

While this information is important in its own right, the first real question was what can we *do* to increase the probability of transfer? The results of this study showed that, conditional on latent transfer subtype, and student background characteristics, exposure to Remediation was negatively associated with transfer, while increases in First-Year GPA and student Engagement were positively associated with transfer. My results regarding these malleable factors were similar to others with respect to first-year GPA, add to the growing research pointing to the negative effects of Remediation, and provide support for the role of Engagement in facilitating transfer. That these malleable factors predict transfer suggests that these are areas in which community colleges could potentially *do* something to increase the probability of transfer.

Similar to the study on the differential effects of Head Start (Cooper & Lanza, 2014), the next question was do these relationships hold for students in different transfer subtypes? The results of this study showed that for students in Class 1*: High Transfer Intentions, Few Barriers* all three malleable variables were strongly associated with transfer likelihood, particularly lack of exposure to Remediation. However, for students in *Class 3: Moderate Transfer Intentions, Low Academic Resources*, the results indicated that none of the malleable variables were statistically significantly related to transfer; only First Generation status was. With respect to *Class 4: Moderate Transfer Intentions, Low Academic Momentum*, again, only First Generation Status was statistically significantly related to transfer (p <.05). However, as mentioned previously, student Engagement was associated with transfer at an inflated alpha of .10. And, as mentioned before, *Class 2: Low Transfer Intentions, Some Barriers* is unaffected by any of these variables given that, effectively, students do not transfer in this transfer subtype.

With respect to the two questions posed, this study not only identified three variables that community colleges could target in order to increase transfer rates, but also provided guidance as to which transfer subtypes are more or less likely to benefit from interventions aimed at changing these variables. Using this information, community colleges could target interventions toward those most likely to benefit, rather than inefficiently assuming that one size fits all.

Methodologically, this dissertation tested the viability of using a latent class structural equation model, in conjunction with the unbiased three-step approach, to identify hypothesized transfer subtypes. Substantively, the structural results of this study more or less agreed with previous studies regarding the factors that predict transfer. However, this study expanded the understanding of how those relationships varied across different transfer subtypes. In addition, this study provided practical advice and an example of the potential benefits associated with using latent class analysis to more strategically target interventions aimed at increasing community college transfer rates to four-year institutions.

5.1: Answers to Research Questions

The statistical analyses conducted in this dissertation were designed to answer the following research questions presented in Chapter 1:

1. *(a) Based upon students' statuses with respect to (i) academic resources, (ii) transfer intentions, (iii) external demands, and (iv) academic momentum, can a latent class analysis identify meaningful transfer subtypes, which are qualitatively distinct across and relatively homogenous within subtype?*

Reflected by the items representing the four above mentioned domains, the Latent Class Analysis revealed transfer subtypes of students who were fairly homogenous within classes, yet substantively different across classes. Moreover, each class differed in at least one substantively interpretable way from at least one other class.

(b) Using appropriate fit indices (i.e., BIC, aBIC, LMR-LRT, etc.) and substantive

interpretability as guides, what is the optimal number of latent classes that describe the observed response patterns?

Based on a comprehensive review of the information criteria, absolute fit statistics, and other relative fit indices, a four class solution fit the data best and provided four substantively relevant classes which I labeled as follows: *Class 1:High Transfer Intention, Few Barriers, Class 2: Low Transfer Intentions, Some Barriers, Class 3: Moderate Transfer Intentions, Low Academic Resources, Class 4: Moderate Transfer Intentions, Low Academic Momentum.*

(c) How precisely does the resulting latent class model classify students into the transfer subtype latent classes?

Overall, the final latent class solution resulted in moderate classification precision (Entropy = .75). At the class level, average posterior class probabilities were all above .70 (Nagin, 2005), ranging from .77 in Class 2 to .94 in Class 1. Additionally, the odds of correct classification were high ranging from 14.2 in Class 1 to 24.1 in Class 2.

(d) Does the latent class model possess measurement invariance (configural, metric/scalar invariance) across Gender, First Generation College Status, and Minority Status?

The latent class model showed an acceptable degree of measurement invariance across Gender, First Generation College Status, and Minority Status. However, the fit indices disagreed as to whether the measurement invariant or non-invariant models fit the data better. On the one hand, the likelihood ratio chi-square difference test indicated that the measurement non-invariant models fit the data better than the constrained models. Conversely, *BIC* preferred the measurement invariant model in each case.

Based on the recommendations of Kankaraš et al. (2010), who advocates reliance on *BIC*, rather than the likelihood ratio chi-square difference test, and upon an examination of the differences in estimated item response probabilities across the measurement invariant and measurement non-invariant models, I concluded that the statistically significant differences were not substantively important differences (Collins & Lanza, 2010).

(e) Are there any direct effects from covariates to latent class indicators?

There were six direct effects from covariates to latent class indicators. In addition to the latent class variable, not being a first generation college student was associated with increased degree expectations and transfer intentions. In addition, being White or Asian was associated with increased financial dependence, less likelihood of working full-time and lower degree aspirations. Finally, again conditional on the latent variable, being Female was highly correlated with greater financial independence and having dependents.

2. *(a) Does a confirmatory factor analysis model support the hypothesis that the NCES academic engagement index can instead be modeled as a latent factor reflected by the same four indicators?*

The strong results from the confirmatory factor analysis supported the hypothesis that the NCES academic engagement index can be modeled as a latent factor. All four observed indicators had moderate to strong factor loadings, and the overall fit of the model was excellent.

(b) Does the latent engagement factor possess measurement invariance (configural, metric/scalar invariance) across Gender, First Generation College Status, and

Minority Status?

The latent engagement factor showed *metric/scalar* (and *configural*) measurement invariance across Gender, First Generation Status, and Minority Status. The likelihood ratio chi-square difference tests confirmed that the *metric/scalar* model did not result in a statistically significant reduction in model fit compared to the *configural* model.

3. *(a) Using the 3-step procedure, does Gender, First Generation College Status, and Minority Status predict latent class membership?*

Only Minority Status was statistically significantly associated with latent class membership. Specifically, White or Asian students were statistically significantly less likely to be classified in *Class 4: Moderate Transfer Intentions, Low Academic Momentum* than in either Classes 2 or 3. However, while both the regression coefficient and the likelihood ratio chi-square difference test showed a statistically significant relationship between Minority Status and Latent Class membership, *BIC* was lower for the model that did not include Minority Status.

(b) Does conditional Latent Class membership predict first-year GPA, Academic Engagement, Remediation, and Transfer?

Latent Class membership was statistically significantly related to first-year GPA, Academic Engagement and Transfer; Remediation proportions, however, were not statistically significantly different across any of the Latent Classes. With the exception of Remediation, the relationships between latent class membership and the above mentioned variables were as expected, thus providing further support for the construct validity of the latent transfer subtype model. Of primary interest, the proportion of community college students who transferred to four-year institutions varied significantly, and in expected ways, across the latent transfer subtypes.

(c) Conditional on latent class membership (i.e., estimating class-specific intercepts) does First-Year GPA, Academic Engagement, and Remediation predict transfer probabilities?

Controlling for Latent Transfer subtype, and student background characteristics, First-Year GPA, Student Engagement, and Remediation were statistically significantly related to transfer likelihood. Additionally, though not statistically significantly related to latent class membership, First Generation College Status also was predictive of transfer.

d) Allowing intercepts and slopes to vary across classes, does latent class membership moderate the relationships between, student background, First-Year GPA, Academic Engagement, Remediation and Transfer?

The results suggest that latent class membership moderates the relationships between student background, First-Year GPA, Academic Engagement, Remediation and Transfer. When class-specific intercepts and slopes were estimated, the effects of Remediation, First-year GPA and Student Engagement were statistically significantly associated with transfer in *Class 1: High Transfer Intention, Few Barriers*, but were not statistically significantly related to transfer in Classes 3 and 4 (Class 2 was not estimated). Moreover, in Class 1 the effect sizes associated with First-Year GPA, Student Engagement and Remediation increased from the model in which slopes were fixed across latent transfer subtypes. Conversely, First-Generation college status was the only statistically significant predictor of transfer (p <.05) among students in Classes 3 and 4; and the magnitude of the effect had increased from the model with slopes fixed across latent classes. Finally, in Class 4, student engagement was statistically significantly (α =.10) associated with transfer (p = .07).

4. *Does the use of latent class analysis and the results of the structural models have practical implications for interventions aimed at increasing transfer rates?*

The results of this study suggest that a latent class analysis could be a useful lens through which to examine how the structural relationships between malleable factors and transfer differ among transfer subtypes. Substantively, for students in *Class 1: High Transfer Intentions, Few Barriers*, community colleges should focus on interventions aimed primarily at decreasing the number of students placed into remedial courses. This is especially relevant for students in Class 1, given that they had the highest incoming academic resources, were most likely to enroll in a remedial course, and clearly intend to transfer. Additionally, with respect to Class 1, the results suggest that community colleges also should provide interventions aimed at increasing First-year GPA, as well as opportunities for greater Student Engagement.

For students in *Class 2: Low Transfer Intentions, Some Barriers,* the latent class analysis successfully identified a transfer subtype that was uninterested in transfer, and essentially, did not transfer. With respect to Class 2, the results indicate that there may be little community colleges could do to increase transfers, other than target interventions toward increasing the transfer intentions of students in this transfer subtype.

With respect to *Class 3: Moderate Transfer Intentions, Low Academic Resources,* the results suggest that community college interventions should be targeted toward programs that address the needs of First Generation College Students. Beyond that, the results are unclear as to whether interventions aimed at reducing remediation, increasing first-term GPA, or increasing opportunities for Student Engagement would make a difference in transfer outcomes.

Regarding *Class 4: Moderate Transfer Intentions, Low Academic Momentum,* the results suggest, as in the case of Class 3, that community colleges should focus their interventions toward meeting the needs of First-Generation College Students; this is particularly important for students in Class 4 given the magnitude of the effect size. In addition, though not statistically significant at the .05 level (p=.07), there is some evidence to suggest that students in Class 4, specifically, would be more likely to transfer if community colleges found a way to increase opportunities for student engagement.

5.2: Contribution to Scholarship

The findings in this study build upon earlier research that examined the relationships between student background characteristics, academic resources, transfer intentions/degree expectations, external demands, academic momentum, college academic performance, remediation, student engagement and community college transfer to four-year institutions (Adelman, 2005a; Crisp & Delgado, 2014; Davidson, 2015; Dougherty & Kienzl, 2006; Dowd et al., 2008; Doyle, 2011; Hagedorn et al., 2008; Hughes & Graham, 1992; Kalogrides & University of California, 2008; Lee & Frank, 1990; Nora & Rendon, 1990; Rendon, 1995; Wang, 2012).

While some of these transfer studies included latent variables, the current study appears to be the first to use a latent class measurement model to measure students' hypothesized latent transfer subtypes. Substantively, based on the findings of the aforementioned studies, this study adds to the literature by developing and testing a community college transfer subtype measurement scale using the robust model-based technique of latent class analysis (Collins & Lanza, 2010; Lazarsfeld & Henry, 1968; Vermunt, Magidson, Hagenaars, & McCutcheon, 2002).

Based on a thorough examination of fit statistics, conditional item response probabilities, tests for local independence, classification quality, and substantive interpretability, the results suggest that the transfer subtype scale developed and tested in this study is a valid measure of what I called transfer subtypes. Furthermore, measurement invariance was assessed across Gender, First Generation College Status and Minority Status. The results provided adequate evidence that the latent transfer subtype measurement model was invariant across these demographics. In addition, the construct validity of the latent transfer subtype measurement model was further supported by the clear and strong relationships between latent transfer subtype and First-term GPA, Engagement, and, most importantly, Transfer.

This study also examined whether the indicators used to create the NCES Academic Integration Index could be used to measure a latent variable, which I referred to as Engagement in this study. Based on the statistical tests and values of absolute and relative fit indices, the results provide strong support for this measurement model. Moreover, the Engagement factor possessed *scalar* measurement invariance across Gender, First Generation Status, and Minority Status. In addition, while the literature has been somewhat mixed regarding the relationship between Engagement and Transfer, this study showed that Engagement was predictive of four-year transfer, and that its effects varied by transfer subtype.

Methodologically, this is the first transfer study to use the three-step approach to examining predictors of latent class and latent class prediction, which both preserves the original meanings of the latent classes and accounts for unreliability in classification (Asparouhov & Muthén, 2014a; Vermunt, 2010). Using this approach, this study further contributed to the transfer literature by examining the differential relationships between first-year GPA, Remediation, and Student Engagement across different Transfer Subtypes. Unlike some other studies, this dissertation found that the effect of Remediation, though generally negative, was particularly deleterious for students in *Class 1: High Transfer Intentions, Few Barriers*. However, when class specific slopes were estimated, Remediation was not statistically significantly related to transfer for students in *Class 3: Moderate Transfer Intentions, Low Academic Resources* or *Class 4: Moderate Transfer Intentions, Low Academic Momentum*. Similar results were obtained regarding first-year GPA and Engagement—these variables were only statistically significantly related to transfer in Class 1, though engagement was statistically significantly related to transfer at an alpha of .10 in Class 4.

In sum, this study makes two primary contributions to the transfer literature. First, this study developed, tested, and validated a latent class transfer subtype measurement model, which could be used by community colleges to design targeted interventions specific to each transfer subtype. Second, using the three step modeling approach, the substantive results showed that the relationships between Remediation, First-Year GPA, Engagement and Transfer vary by transfer subtype. That these relationships are not the same across latent subtypes, provides a more nuanced answer to the question of whether these variables predict transfer or not. For some subtypes they do predict transfer, for others, they seem to be less important.

5.3: Limitations of the Study

The findings from this study are limited by the correlational nature of the relationships found among the latent and observed variables. Though the latent class structural equation model identified several statistically significant relationships between temporally precedent predictors and transfer, the study does not control for confounding as in randomized trials or other counterfactual designs. Therefore, the findings of this study do not establish causal relationships between the latent and observed variables and community college transfer to four-year institutions. Additionally, that I identified and gave names to four latent classes and one continuous latent factor, neither proves that these constructs exist nor that I have properly named them (Kline, 2005). Relatedly, even though the latent class structural equation model implied representation of the data in this study was plausible, several alternative models may exist. These alternate models may explain the relationships between the variables in this study as well as or better than the chosen models.

The findings of this study were further limited by the data available in the BPS:04/09 dataset. First, the dataset lacked several important high school academic performance measures. For example, high school test scores were unavailable for all students. In addition, high school GPA was only available for students who took the SAT or ACT. For students 24 years of age and older, no high school information was available, including whether or not students took the SAT or ACT. In fact, the dataset was so sparse with respect to students 24 years of age and older, that they were not included in the analysis. Therefore, this study is limited in its external validity to students under the age of 24.

With respect to college level variables, the dataset did not include college placement test scores, the specific courses students enrolled in, nor the grades and units received in those courses. Such information could have facilitated a more robust analysis of how the relationships between first-year course-taking, performance and transfer varied across transfer subtypes. In addition, while there were some indicators of general academic engagement, the indicators available were insufficient to measure the more multidimensional conception of engagement cited in the literature.

Although the overall sample size in this study, 3,940, is quite large, it is unclear whether some of the latent-class specific regressions performed in smaller classes had enough power to detect small effect sizes. This is an area for further research.

Finally, while the three-step approach to latent class structural equation modeling as implemented in Mplus 7.3 is fairly flexible, the current software capabilities precluded a multi-level latent class analysis of the data. Although I controlled for the complex sampling design, a model based approach would have allowed for an examination of the potentially differential effects of institutional policies and student composition on the probability of transfer. In particular, a multilevel latent class structural equation model could have helped to assess, for example, whether larger proportions of part-time faculty—perhaps the most promising of studied institutional variables—affect the odds of transfer differently across latent transfer subtypes.

5.4: Implications for Practice and Intervention

The two primary goals of this study were, first, to test whether a latent class analysis could identify substantively interpretable transfer subtypes and second, to assess whether the relationships between malleable factors and community college transfer varied across the hypothesized transfer subtypes. The results suggest that the latent transfer subtype measurement model fits the data well, provides substantively interpretable and useful classifications of students, and has evidence to support its construct validity.

Notwithstanding the above mentioned limitations, while the instrument would need further refinements, future replications, as well as local college validation studies, the results of this study, based on a nationally representative sample of community college students, suggest that community colleges at the time of registration, could use a transfer subtype instrument to classify students into a substantively meaningful transfer subtype class. Once assigned to a transfer subtype, community colleges could provide students with class-specific advisement and/or interventions.

In other words, while this study generally does not provide policy-makers with the specifics of potential interventions, it does provide underfunded community colleges with advice as to where and to whom potential transfer interventions should be focused. For example, while reducing remediation among students with high academic resources, transfer intentions, academic momentum, and low external demands should result in significant increases in transfer rates, the same action taken among students with low academic resources, transfer intentions, academic momentum and high external demands may have no effect on transfer rates.

Generally speaking, the implications of this study for policy makers are that remediation, first-year College GPA, and student engagement are three malleable factors that affect transfer rates. However, the relationships between these malleable factors and transfer vary across the four subtypes of students identified in this study. Using such information, community colleges may be better poised to, first, focus their scarce resources on interventions aimed at variables that actually affect transfer, and, second, target their interventions to the students for whom these variables are most likely to affect transfer outcomes.

Substantively, with respect to the transfer subtypes identified in this study, there are five potential implications for practice. First, the predicted probability of transfer for students classified into *Class 2: Low Transfer Intentions, Some Barriers* was less than .02.

This finding suggests that students in Class 2, as they indicated, truly did not intend to transfer. Practically, this finding implies that, other than changing students' transfer intentions, community colleges may be unable to affect transfer rates among students who do not intend to transfer. Therefore, community colleges might consider supporting these students in completing their non-transfer goals, rather than allocating resources toward increasing their transfer likelihoods.

Second, for students in *Class 1: High Transfer Intentions, Few Barriers*, the results suggest that community colleges should design interventions targeted at increasing opportunities for Engagement, assuring students succeed academically during their first year, and, perhaps most importantly, consider placing these students directly into college level courses, rather than into remedial courses. Practically, perhaps the most cost effective policy change that community colleges could make to increase transfer rates would be to place students, who are academically prepared, have few external demands, and have high transfer intentions, directly into college level courses.

Class 1 was the largest class comprised of students who had the highest academic resources, strongest transfer intentions, fewest external demands, and highest academic momentum, yet they were most likely to have taken a remedial course during their first year. Further, the odds of transfer for a student in Class 1 who did not take a remedial class, compared to a student who did, were more than double (OR=2.1). Accordingly, again, these results suggest that community colleges could greatly increase transfer rates simply by placing fewer students, who share the characteristics of students in Class 1, into remedial courses.

Fourth, though generally applicable, the negative effects of first generation college status on transfer was most pronounced among students classified into *Class 3: Moderate Transfer Intentions, Low Academic Resources*, and especially *Class 4: Moderate Transfer Intentions, Low Academic Momentum*. Students in Class 3 had moderate transfer intentions and the lowest academic resources of any subtype. Students in Class 4 had the highest degree of external demands and were least likely to be enrolled full-time. This finding suggests that, to increase transfer rates among students assigned to Classes 3 and 4, community colleges should design interventions aimed at meeting the needs of first-generation college students.

Finally, as mentioned, though the finding is weakly supported, this study provides some evidence that Engagement is predictive of transfer among students in *Class 4: Moderate Transfer Intentions, Low Academic Momentum*. This finding suggests that increasing engagement for students who are more likely to be enrolled part-time and have greater external demands, may increase transfer rates.

5.5: Areas for Further Research

First, as mentioned in the limitations section, there are several community college course-taking variables that are unavailable in the BPS:04/09. For example, some studies have shown that taking particular courses early on or completing threshold numbers of units in a given timeframe are related to transfer outcomes (Adelman, 2005a; Attewell et al., 2012; Leinbach & Jenkins, 2008). Therefore, an area for future research could involve testing whether latent transfer subtypes achieve different transfer outcomes based on which courses they take and when, as well as how many units they complete in a given time period.

This study showed that student engagement was predictive of transfer, but due to dataset limitations, only one narrow dimension of engagement was measured. Future studies might expand upon this finding to explore whether the relationships between different dimensions of student engagement, as measured by the Community College Survey of Student Engagement (Marti, 2004, 2006; McClenney et al., 2012), and transfer vary across transfer subtypes.

In addition, this study examined the direct effects of student engagement on transfer, controlling for first-year GPA, rather than the possible indirect effects of student engagement on transfer mediated by first-year GPA. It would be an interesting follow-up study to assess the change in the magnitude of the direct effect of student engagement on transfer when mediated by first-year GPA. If the effects of engagement are largely mediated through first-year GPA, then interventions aimed at increasing first-year GPA could include increasing engagement, but if the reduction in the size of the direct effect is insignificant or small, then different interventions would be needed to increase first-year GPA (Jose, 2013). Further, it would be useful then to know if the degree of possible mediation is moderated by latent transfer subtype membership.

This study also found, similar to Dougherty and Kienzl (2006), that First Generation College Status was negatively associated with transfer. An important area for future research would be to investigate through what means this variable affects transfer rates given that First-Generation status did not predict latent class membership, but did predict transfer. Future studies might examine whether the effects of first-generation status on transfer are mediated by GPA, Engagement, Remediation, or other variables in the study.

This study found that, when only class specific intercepts were estimated, exposure to Remediation was negatively associated with four-year transfer across all classes. When class specific slopes were estimated, the negative relationship between Remediation and transfer remained statistically significant and increased in magnitude only in *Class 1: High Transfer Intentions, Few Barriers*. Focusing on students in Class 1, research exploring the placement cut scores or other mechanisms that directed these students—the students with the highest academic resources—to remediation could help elucidate what types of interventions to employ or policies to change.

Continuing with Remediation and focusing on students who were directed to Remediation in Class 1, it would be interesting to randomly assign students to either remediation or college level coursework, and then assess their outcomes. However, I would only suggest including students in Class 1 who were close to the cutoff between remediation and college level coursework. These students, for all intents and purposes, are the most academically capable of community college students and perhaps the most misplaced (Belfield & Crosta, 2012; Willett, 2013).

Admittedly, randomized trials are rarely used in educational research due to legal constraints and/or moral reasons (Cook & Payne, 2002). However, this has always troubled me given what millions of Community College students across the United States have to lose in terms of financial, societal and health benefits by not transferring to a four-year institution (Attewell, Lavin, Domina, & Levey, 2006). With respect to remediation, a growing literature, including this study points to poor outcomes for students who are exposed to remediation, though not all studies have come to the same conclusion (Bahr, 2008b; Bettinger & Long, 2005). A randomized trial could help to answer this question.

Future research could expand the current study to include a multilevel analysis in which institutional level variables and their effects on transfer could be examined across latent transfer subtypes. Moreover, level two latent classes could be specified to group colleges into similar transfer subtypes based on random level 1 intercepts. In other words, similar to Henry and Muthén (2010), at level 2 community colleges could be grouped on the basis of similar level 1 latent class prevalences into classes that reflect the differing proportions of transfer subtypes that exist in each college. Using these level 2 latent classes, researchers could then examine the potentially differential effects of part-time faculty, tuition, expenditures, etc. on transfer likelihood.

In addition, community colleges are increasingly under the scrutiny of several external auditors and stakeholders who demand accountability. Most accountability systems include transfer outcomes as a central measure of institutional effectiveness (House, 2012). However, most of these systems do not control for the student characteristics of the community college when assessing transfer rates. A potentially equitable means of comparing community college transfer rates could involve comparing transfer rates within the same latent transfer subtype across colleges.

For example, imagine if the majority of students in community college “x” were classified into *Class 2: Low Transfer Intentions, Some Barriers*, which have a predicted probability of transfer of less than .02. By contrast, in college “y” the majority of students are classified into *Class 1: High Transfer Intentions, Few Barriers*, which have a predicted probability of transfer of .43. To compare transfer rates between colleges x and y without first adjusting for transfer subtype would be meaningless at best. However, to compare transfer rates within transfer subtypes across colleges might provide for a meaningful and “equitable” comparison. This is an area for further research.

Finally, future research should find a way to include in their analyses students who are 24 years of age and older. The BPS: 04/09 provided very little high school performance information for older students, and thus I was unable to include these students in my analysis. Nearly 28% of community college beginners in this study were 24 years of age. Future research should examine whether the latent transfer subtype factor is invariant across age or whether a different model is required for this significant proportion of community college students.

5.6: Final Thoughts

Community College transfer to four-year institutions depends on a complex array of student background characteristics, behaviors, as well as college policies and procedures. This study attempted to reduce this complexity by classifying students into four parsimonious transfer subtypes. The results showed that one way underfunded community colleges might address low transfer rates is by examining how the relationships between malleable factors and transfer vary across transfer subtypes. Through strategic planning and targeted efforts, perhaps community colleges can realize their great potential to foster equality of not only access, but also educational outcomes, including four-year transfer.

REFERENCES

Adelman, C. (1999). *Answers in the Tool Box: Academic Intensity, Attendance Patterns, and the Bachelor's Degree Attainment*.

Adelman, C. (2005a). Moving into Town--and Moving On: The Community College in the Lives of Traditional-Age Students. *US Department of Education*.

Adelman, C. (2006). *The toolbox revisited: Paths to degree completion from high school through college (report)*.

Adelman, C., Daniel, B., Berkovits, I., & Owings, J. (2003). *Postsecondary attainment, attendance, curriculum, and performance: Selected results from the NELS:1988/2000 postsecondary education transcript study (NCES 2003–394)* (Vol. null).

Agresti, A. (2013). *Categorical data analysis*: John Wiley & Sons.

Akaike, H. (1987). Factor analysis and AIC. *Psychometrika, 52*(3), 317-332.

Akaike, H., Petrov, B. N., & Csaki, B. F. (1973). *Second International Symposium on Information Theory* (Vol. null).

Alexander, K., Bozick, R., & Entwisle, D. (2008). Warming up, cooling out, or holding steady? Persistence and change in educational expectations after high school. *Sociology of Education, 81*(4), 371-396.

Alfonso, M. (2006). The impact of community college attendance on baccalaureate attainment. *Research in Higher Education, 47*(8), 873-903.

Alfonso, M., Bailey, T. R., & Scott, M. (2005). The educational outcomes of occupational sub-baccalaureate students: evidence from the 1990s. *Economics of Education Review, 24*(2), 197-212.

Allen, D., & Dadgar, M. (2012). Does dual enrollment increase students' success in college? Evidence from a quasi-experimental analysis of dual enrollment in New York City. *New Directions for Higher Education, 2012*(158), 11-19. doi: 10.1002/he.20010

Allen, J., Robbins, S. B., Casillas, A., & Oh, I.-S. (2008). Third-year college retention and transfer: Effects of academic performance, motivation, and social connectedness. *Research in Higher Education, 49*(7), 647-664.

Anderson, G. M., Sun, J. C., & Alfonso, M. (2006). Effectiveness of Statewide articulation agreements on the probability of transfer: A preliminary policy analysis (vol 29, pg 261, 2006). *Review of Higher Education, 29*(4), 1.

Asparouhov, T. (2006). General multi-level modeling with sampling weights. *Communications in Statistics—Theory and Methods, 35*(3), 439-460.

Asparouhov, T., & Muthén, B. (2011). *Using Bayesian priors for more flexible latent class analysis.* Paper presented at the Proceedings of the 2011 Joint Statistical Meeting, Miami Beach, FL.

Asparouhov, T., & Muthén, B. (2012). Using Mplus TECH11 and TECH14 to test the number of latent classes. *Mplus web notes*(14).

Asparouhov, T., & Muthén, B. (2013). Auxiliary variables in mixture modeling: 3-step approaches using Mplus. *Mplus web notes, 15*, 1-24.

Asparouhov, T., & Muthén, B. (2014a). Auxiliary Variables in Mixture Modeling: Three-Step Approaches Using M plus. *Structural Equation Modeling: A Multidisciplinary Journal, 21*(3), 329-341.

Asparouhov, T., & Muthén, B. (2014b). Auxiliary Variables in Mixture Modeling: Using the BCH Method in Mplus to Estimate a Distal Outcome Model and an Arbitrary Secondary Model.

Astin, A. W. (1999). Student involvement: A developmental theory for higher education.

Attewell, P., Heil, S., & Reisel, L. (2012). What Is Academic Momentum? And Does It Matter? *Educational Evaluation and Policy Analysis, 34*(1), 27-44. doi: 10.3102/0162373711421958

Attewell, P., Lavin, D., Domina, T., & Levey, T. (2006). New evidence on college remediation. *Journal of Higher Education*, 886-924.

Bahr, P. (2008a). Cooling Out in the Community College: What is the Effect of Academic Advising on Students' Chances of Success? *Research in Higher Education, 49*(8), 704-732.

Bahr, P. (2009). Educational Attainment as Process: Using Hierarchical Discrete-Time Event History Analysis to Model Rate of Progress. *Research in Higher Education, 50*(7), 691-714.

Bahr, P. R. (2008b). Does mathematics remediation work?: A comparative analysis of academic attainment among community college students. *Research in Higher Education, 49*(5), 420-450.

Bahr, P. R., Toth, C., Thirolf, K., & Massé, J. C. (2013). A review and critique of the literature on community college students' transition processes and outcomes in four-year institutions *Higher Education: Handbook of Theory and Research* (pp. 459-511): Springer.

Bailey, T., Calcagno, J. C., Jenkins, D., Leinbach, T., & Kienzl, G. (2006). Is student-right-to-know all you should know? An analysis of community college graduation rates. *Research in Higher Education, 47*(5), 491-519.

Bailey, T. R., Crosta, P. M., & Jenkins, P. D. (2006). What Can Student Right-to-Know Graduation Rates Tell Us About Community College Performance?

Belfield, C., & Crosta, P. M. (2012). Predicting success in college: The importance of placement tests and high school transcripts.

Belfield, C. R., & Bailey, T. (2011). The Benefits of Attending Community College: A Review of the Evidence. *Community College Review, 39*(1), 46-68. doi: 10.1177/0091552110395575

Benjamin, E. (2003). Reappraisal and implications for policy and research. *New Directions for Higher Education, 2003*(123), 79-113.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238.

Bergman, L. R., Magnusson, D., & El Khouri, B. M. (2003). *Studying individual development in an interindividual context: A person-oriented approach*: Psychology Press.

Berkner, L., & Choy, S. (2008). Descriptive Summary of 2003-04 Beginning Postsecondary Students: Three years Later (NCES 2008-174). Washington, DC: National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education.

Bettinger, E. P., & Long, B. T. (2005). Remediation at the community college: Student participation and outcomes. *New Directions for Community Colleges, 2005*(129), 17-26.

Black, D. A., & Smith, J. A. (2006). Estimating the returns to college quality with multiple proxies for quality. *Journal of Labor Economics, 24*(3), 701-728.

Bolck, A., Croon, M., & Hagenaars, J. (2004). Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis, 12*(1), 3-27.

Bozdogan, H. (1987). Model selection and Akaike's information criterion (AIC): The general theory and its analytical extensions. *Psychometrika, 52*(3), 345-370.

Bradburn, E. M., Hurst, D. G., & Peng, S. (2001). *Community college transfer rates to 4-year institutions using alternative definitions of transfer (NCES 2001–197).*

Brand, J. E. (2010). Civic returns to higher education: A note on heterogeneous effects. *Social Forces, 89*(2), 417-433.

Brand, J. E., Pfeffer, F., & Goldrick-Rab, S. (2012). Interpreting Community College Effects in the Presence of Heterogeneity and Complex Counterfactuals. *California Center for Population Research*.

Brand, J. E., & Xie, Y. (2010). Who benefits most from college? Evidence for negative selection in heterogeneous economic returns to higher education. *American Sociological Review, 75*(2), 273-302.

Bray, B. C., Lanza, S. T., & Tan, X. (2014). Eliminating bias in classify-analyze approaches for latent class analysis. *Structural Equation Modeling: A Multidisciplinary Journal*(ahead-of-print), 1-11.

Brint, S., & Karabel, J. (1989). *The diverted dream: Community colleges and educational opportunity in America, 1900–1985*.

Brown, T. A. (2014). *Confirmatory factor analysis for applied research*: Guilford Publications.

Browne, M. W., Cudeck, R., Bollen, K. A., & Long, J. S. (1993). Alternative ways of assessing model fit. *Sage Focus Editions, 154*, 136-136.

Calcagno, J., Crosta, P., Bailey, T., & Jenkins, D. (2007). Stepping Stones to a Degree: The Impact of Enrollment Pathways and Milestones on Community College Student Outcomes. *Research in Higher Education, 48*(7), 775-801.

Calcagno, J. C., Bailey, T., Jenkins, D., Kienzl, G., & Leinbach, T. (2008). Community college student success: What institutional characteristics make a difference? *Economics of Education Review, 27*(6), 632-645.

Calcagno, J. C., & Long, B. T. (2008). *The impact of postsecondary remediation using a regression discontinuity approach: Addressing endogenous sorting and noncompliance*.

Cavrini, G., Galimberti, G., & Soffritti, G. (2009). Evaluating patient satisfaction through latent class factor analysis. *Health & Place, 15*(1), 210-218. doi: http://dx.doi.org/10.1016/j.healthplace.2008.04.007

Chen, R. (2012). Institutional Characteristics and College Student Dropout Risks: A Multilevel Event History Analysis. *Research in Higher Education, 53*(5), 487-505. doi: 10.1007/s11162-011-9241-4

Chung, H., & Anthony, J. C. (2013). A Bayesian Approach to a Multiple-Group Latent Class-Profile Analysis: The Timing of Drinking Onset and Subsequent Drinking Behaviors Among US Adolescents. *Structural Equation Modeling: A Multidisciplinary Journal, 20*(4), 658-680.

Clark, B. R. (1960). The" cooling-out" function in higher education. *American journal of Sociology*, 569-576.

Clark, B. R. (1980). The “cooling out” function revisited. *New Directions for Community Colleges, 1980*(32), 15-31.

Clark, S. L. (2010). *Mixture* modeling with behavioral data*: University of California, Los Angeles.

Clark, S. L., & Muthén, B. (2009). Relating latent class analysis results to variables not included in the analysis. *Submitted for publication*.

Clogg, C. C. (1995). Latent class models *Handbook of statistical modeling for the social and behavioral sciences* (pp. 311-359): Springer.

Cohen, A. M., & Brawer, F. B. (2008). *The American community college*. San Francisco: Jossey-Bass.

Cohen, A. M., Brawer, F. B., & Kisker, C. B. (2013). *The American community college*: John Wiley & Sons.

Collins, L. M., & Lanza, S. T. (2010). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences* (Vol. 718): John Wiley & Sons.

Cook, T. D., & Payne, M. R. (2002). Objecting to the objections to using random assignment in educational research. *Evidence matters: Randomized trials in education research*, 150-178.

Cooper, B. R., & Lanza, S. T. (2014). Who Benefits Most From Head Start? Using Latent Class Moderation to Examine Differential Treatment Effects. *Child Development*, n/a-n/a. doi: 10.1111/cdev.12278

Crisp, G., & Delgado, C. (2014). The Impact of Developmental Education on Community College Persistence and Vertical Transfer. *Community College Review, 42*(2), 99-117. doi: 10.1177/0091552113516488

Crisp, G., & Nora, A. (2010). Hispanic Student Success: Factors Influencing the Persistence and Transfer Decisions of Latino Community College Students Enrolled in Developmental Education. *Research in Higher Education, 51*(2), 175-194. doi: 10.1007/s11162-009-9151-x

Crisp, G., & Nuñez, A.-M. (2014). Understanding the Racial Transfer Gap: Modeling Underrepresented Minority and Nonminority Students' Pathways from Two-to Four-Year Institutions. *The Review of Higher Education, 37*(3), 291-320.

Crow, S. (2009). Musings on the future of accreditation. *New Directions for Higher Education, 2009*(145), 87-97. doi: 10.1002/he.338

Davidson, J. C. (2015). Precollege Factors and Leading Indicators: Increasing Transfer and Degree Completion in a Community and Technical College System. *Community College Journal of Research and Practice*(ahead-of-print), 1-15.

De Ayala, R. J. (2009). *The theory and practice of item response theory*. New York; London: Guilford ;.

Deil-Amen, R. (2011). Socio-academic integrative moments: Rethinking academic and social integration among two-year college students in career-related programs. *The Journal of Higher Education, 82*(1), 54-91.

Deil-Amen, R. (2012). *The "traditional" college student: A smaller and smaller minority and its implications for diversity and access institutions*.

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum Likelihood from Incomplete Data via the EM Algorithm. *Journal of the Royal Statistical Society. Series B (Methodological), 39*(1), 1-38.

Desai, S. A. (2011). Is Comprehensiveness Taking Its Toll on Community Colleges?: An In-depth Analysis of Community Colleges' Missions and Their Effectiveness. *Community College Journal of Research and Practice, 36*(2), 111-121. doi: 10.1080/10668920802611211

Dickert-Conlin, S., & Rubenstein, R. H. (2007). *Economic inequality and higher education : access, persistence, and success*. New York: Russell Sage Foundation.

Dougherty, K. J., & Kienzl, G. S. (2006). It's Not Enough to Get Through the Open Door: Inequalities by Social Background in Transfer from Community Colleges to Four-Year Colleges. *Teachers College Record, 108*(3), 452-487.

Dougherty, K. J., & Townsend, B. K. (2006). Community college missions: A theoretical and historical perspective. *New Directions for Community Colleges, 2006*(136), 5-13.

Dowd, A. C. (2003). From Access to Outcome Equity: Revitalizing the Democratic Mission of the Community College. *Annals of the American Academy of Political and Social Science, 586*, 92-119.

Dowd, A. C., Cheslock, J. J., & Melguizo, T. (2008). Transfer Access from Community Colleges and the Distribution of Elite Higher Education. *The Journal of Higher Education, 79*(4), 442-472.

Dowd, A. C. M., Tatiana. (2008). Socioeconomic Stratification of Community College Transfer Access in the 1980s and 1990s: Evidence from HS&B and NELS. *The Review of Higher Education, 31*(4), 377- 400.

Doyle, W. R. (2011). Effect of increased academic momentum on transfer rates: An application of the generalized propensity score. *Economics of Education Review, 30*(1), 191-200.

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology, 53*(1), 109-132.

Enders, C. K. (2010). *Applied missing data analysis*: Guilford Publications.

Finch, W. H., & Bronk, K. C. (2011). Conducting Confirmatory Latent Class Analysis Using M plus. *Structural Equation Modeling, 18*(1), 132-151.

Flora, D. B., & Curran, P. J. (2004). An empirical evaluation of alternative methods of estimation for confirmatory factor analysis with ordinal data. *Psychological Methods, 9*(4), 466.

Folsom, R. E., & Singh, A. C. (2000). *The generalized exponential model for sampling weight calibration for extreme values, nonresponse, and poststratification.* Paper presented at the Proceedings of the American Statistical Association, Survey Research Methods Section.

Fowler, F. J. (2014). Survey Research Methods Fifth Edition. *APPLIED SOCIAL RESEARCH METHODS SERIES, 1*, ALL.

Freeman, M. L. (2007). Gender, Geography, Transfer, and Baccalaureate Attainment. *freeman, 740*, 597-1862.

Ganninger, M. (2010). Design effects: model-based versus design-based approach.

Goble, L. J., Rosenbaum, J. E., & Stephan, J. L. (2008). Do institutional attributes predict individuals' degree success at two-year colleges? *New Directions for Community Colleges, 2008*(144), 63-72.

Goldrick-Rab, S. (2007). Promoting academic momentum at community colleges: Challenges and opportunities.

Green, J. L., Camilli, G., Elmore, P. B., & American Educational Research, A. (2006). *Handbook of complementary methods in education research*. Mahwah, N.J.; Washington, D.C.: Lawrence Erlbaum Associates ; Published for the American Educational Research Association.

Greene, T. G. (2005). *Bridging the great divide: Exploring the relationship between student engagement and educational outcomes for African American and Hispanic community college students in the state of Florida* (Vol. null).

Grubb, W. N. (1991). The Decline of Community College Transfer Rates: Evidence from National Longitudinal Surveys. *The Journal of Higher Education, 62*(2), 194-222. doi: 10.2307/1982145

Hagedorn, L. S., Cypers, S., & Lester, J. (2008). Looking in the Review Mirror: Factors Affecting Transfer for Urban Community College Students. *Community College Journal of Research and Practice, 32*(9), 643-664. doi: 10.1080/10668920802026113

Hambleton, R. K., Swaminathan, H., & Rogers, H. J. (1991). *Fundamentals of item response theory*. Newbury Park, Calif.: Sage Publications.

Handel, S. J. (2013). The Transfer Moment: The Pivotal Partnership Between Community Colleges and Four-Year Institutions in Securing the Nation's College Completion Agenda. *New Directions for Higher Education, 2013*(162), 5-15.

Hanushek, E. A., Kain, J. F., Markman, J. M., & Rivkin, S. G. (2003). Does peer ability affect student achievement? *Journal of applied econometrics, 18*(5), 527-544.

Harbour, C. P., & Smith, D. A. (2015). The Completion Agenda, Community Colleges, and Civic Capacity. *Community College Journal of Research and Practice*(ahead-of-print), 1-15.

Heck, R. H., & Thomas, S. L. (2015). *An Introduction to Multilevel Modeling Techniques*: Routledge.

Henry, K. L., & Muthén, B. (2010). Multilevel latent class analysis: An application of adolescent smoking typologies with individual and contextual predictors. *Structural Equation Modeling, 17*(2), 193-215.

Herd, P., Goesling, B., & House, J. S. (2007). Socioeconomic position and health: the differential effects of education versus income on the onset versus progression of health problems. *Journal of Health and Social Behavior, 48*(3), 223-238.

Hom, W. C. (2009). The denominator as the “target”. *Community College Review, 37*(2), 136-152.

Horn, L. (2009). On track to complete?: a taxonomy of beginning community college students and their outcomes 3 years after enrolling: 2003-04 through 2006.

Horn, L., & Skomsvold, P. (2011). Community college student outcomes: 1994-2009.

Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (Vol. 398): John Wiley & Sons.

House, W. (2012). College scorecard. *Washington, DC: White House*.

Hout, M. (2012). Social and Economic Returns to College Education in the United States. *Annual Review of Sociology, 38*(1), 379-400. doi: doi:10.1146/annurev.soc.012809.102503

Hox, J. J., & Roberts, J. K. (2011). *Handbook of advanced multilevel analysis*. New York: Routledge.

Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55.

Huang, D., Brecht, M.-L., Hara, M., & Hser, Y.-I. (2010). Influences of covariates on growth mixture modeling. *Journal of drug issues, 40*(1), 173-194.

Hughes, J. A., & Graham, S. W. (1992). Academic Performance and Background Characteristics Among Community College Transfer Students. *Community Junior College Research Quarterly of Research and Practice, 16*(1), 35-46. doi: 10.1080/0361697920160104

Hungar, J., & Lieberman, J. (2001). *The Road to Equality: Report on Transfer*.

Ishitani, T. T. (2006). Studying attrition and degree completion behavior among first-generation college students in the United States. *Journal of Higher Education*, 861-885.

Jacoby, D. (2006). Effects of Part-Time Faculty Employment on Community College Graduation Rates. *The Journal of Higher Education, 77*(6), 1081-1103.

Jones-White, D., Radcliffe, P., Huesman, R., & Kellogg, J. Redefining Student Success: Applying Different Multinomial Regression Techniques for the Study of Student Graduation Across Institutions of Higher Education. *Research in Higher Education*.

Jones, S. (2012). Time Is Money... and the Enemy of College Completion: Transform American Higher Education to Boost Completion and Reduce Costs. Testimony before the United States House of Representatives Subcommittee on Higher Education and Workforce Training. *Complete College America*.

Jose, P. E. (2013). *Doing statistical mediation and moderation*: Guilford Press.

Kalogrides, D. M., & University of California, D. (2008). *Community College Transfer and Degree Attainment*: University of California, Davis.

Kankaraš, M., Moors, G., & Vermunt, J. K. (2010). Testing for measurement invariance with latent class analysis. *Cross-cultural analysis: Methods and applications*, 359-384.

Karp, M. M., Hughes, K. L., & O'Gara, L. (2010). An exploration of Tinto's integration framework for community college students. *Journal of College Student Retention: Research, Theory and Practice, 12*(1), 69-86.

Kevin Eagan, M., & Jaeger, A. (2009). Effects of Exposure to Part-time Faculty on Community College Transfer. *Research in Higher Education, 50*(2), 168-188.

Kim, D. B. (2007). The effect of loans on students' degree attainment: Differences by student and institutional characteristics. *Harvard Educational Review, 77*(1), 64-100.

Kish, L. (1965). *Survey sampling*.

Kish, L., & Frankel, M. R. (1974). Inference from complex samples. *Journal of the Royal Statistical Society. Series B (Methodological)*, 1-37.

Kline, R. B. (2005). *Principles and practice of structural equation modeling*. New York: Guilford Press.

Knoell, D., & Medsker, L. L. (1965). *From junior to senior college: A national study of the transfer student*.

Kuh, G. D. (2003). What We're Learning About Student Engagement From NSSE: Benchmarks for Effective Educational Practices. *Change: The Magazine of Higher Learning, 35*(2), 24-32. doi: 10.1080/00091380309604090

Kuh, G. D., Cruce, T. M., Shoup, R., Kinzie, J., & Gonyea, R. M. (2008). Unmasking the effects of student engagement on first-year college grades and persistence. *The Journal of Higher Education, 79*(5), 540-563.

Laanan, F. S. (2003). DEGREE ASPIRATIONS OF TWO-YEAR COLLEGE STUDENTS. *Community College Journal of Research and Practice, 27*(6), 495 - 518.

Lange, F., & Topel, R. (2006). The social value of education and human capital. *Handbook of the Economics of Education, 1*, 459-509.

Lanza, S. T., & Rhoades, B. L. (2013). Latent class analysis: An alternative perspective on subgroup analysis in prevention and treatment. *Prevention Science, 14*(2), 157-168.

LaSota, R. R. (2013). *Factors, Practices, and Policies Influencing Students' Upward Transfer to Baccalaureate-Degree Programs and Institutions: A Mixed Methods Analysis.* University of Washington.

Lazarsfeld, P. F., & Henry, N. W. (1968). *Latent structure analysis* (Vol. null).

Lee, S.-Y. (2007). *Structural equation modeling: A Bayesian approach* (Vol. 711): Wiley.

Lee, S.-Y., Song, X.-Y., & Cai, J.-H. (2010). A Bayesian approach for nonlinear structural equation models with dichotomous variables using logit and probit links. *Structural Equation Modeling, 17*(2), 280-302.

Lee, V. E., & Frank, K. A. (1990). Students' Characteristics that Facilitate the Transfer from Two-Year to Four-Year Colleges. *Sociology of Education, 63*(3), 178-193.

Lee, V. E., Mackie-Lewis, C., & Marks, H. M. (1993). Persistence to the Baccalaureate Degree for Students Who Transfer from Community College. *American Journal of Education, 102*(1), 80-114. doi: 10.2307/1085696

Leigh, D. E., & Gill, A. M. (2003). Do community colleges really divert students from earning bachelor's degrees? *Economics of Education Review, 22*(1), 23-30.

Leinbach, D. T., & Jenkins, D. (2008). Using Longitudinal Data to Increase Community College Student Success: A Guide to Measuring Milestone and Momentum Point Attainment. CCRC Research Tools No. 2. *Community College Research Center, Columbia University*.

Lester, J. (2014). The Completion Agenda: The Unintended Consequences for Equity in Community Colleges *Higher Education: Handbook of Theory and Research* (pp. 423-466): Springer.

Little, R. J., & Rubin, D. B. (2014). *Statistical analysis with missing data*: John Wiley & Sons.

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika, 88*(3), 767-778.

Long, B. T., & Kurlaender, M. (2009). Do Community Colleges Provide a Viable Pathway to a Baccalaureate Degree? *Educational Evaluation and Policy Analysis, 31*(1), 30-53. doi: 10.3102/0162373708327756

Lucas, S. R. (2001). Effectively Maintained Inequality: Education Transitions, Track Mobility, and Social Background Effects1. *American journal of Sociology, 106*(6), 1642-1690.

Lynch, S. M. (2007). Introduction to applied Bayesian statistics and estimation for social scientists. from http://public.eblib.com/EBLPublic/PublicView.do?ptiID=602892

MacCallum, R. C., & Austin, J. T. (2000). Applications of Structural Equation Modeling in Psychological Research. *Annual Review of Psychology, 51*(1), 201-226. doi: doi:10.1146/annurev.psych.51.1.201

MacCallum, R. C., Wegener, D. T., Uchino, B. N., & Fabrigar, L. R. (1993). The problem of equivalent models in applications of covariance structure analysis. *Psychological Bulletin, 114*(1), 185-199.

Magidson, J., & Vermunt, J. (2002). Latent class models for clustering: A comparison with K-means. *Canadian Journal of Marketing Research, 20*(1), 36-43.

Magidson, J., & Vermunt, J. K. (2004). Latent class models. *The Sage handbook of quantitative methodology for the social sciences*, 175-198.

Magnusson, D. (2003). The person approach: Concepts, measurement models, and research strategy. *New directions for child and adolescent development, 2003*(101), 3-23.

Marti, C. N. (2004). *Overview of the CCSSE instrument and psychometric properties. Community College Survey of Student Engagement Web site* (Vol. null).

Marti, C. N. (2006). *Dimensions of student engagement in American community colleges: Using the Community College Student Report in research and practice* (Vol. null).

Masyn, K. (2013). Latent class analysis and finite mixture modeling. *The Oxford handbook of quantitative methods in psychology, 2*, 551-611.

McArthur, R. C. (1999). A comparison of grading patterns between full-and part-time humanities faculty: A preliminary study. *Community College Review, 27*(3), 65-76.

McClenney, K., Marti, C. N., & Adkins, C. (2012). Student Engagement and Student Outcomes: Key Findings from" CCSSE" Validation Research. *Community College Survey of Student Engagement*.

McCutcheon, A. L. (1987). *Latent class analysis*: Sage.

McKelvey, R. D., & Zavoina, W. (1975). A statistical model for the analysis of ordinal level dependent variables. *The Journal of Mathematical Sociology, 4*(1), 103-120. doi: 10.1080/0022250X.1975.9989847

McLachlan, G., & Peel, D. (2004). *Finite mixture models*: John Wiley & Sons.

Mehrens, W. A., & Lehmann, I. J. (1987). *Using standardized tests in education*. New York: Longman.

Melguizo, T., Kienzl, G. S., & Alfonso, M. (2011). Comparing the Educational Attainment of Community College Transfer Students and Four-Year College Rising Juniors Using Propensity Score Matching Methods. *The Journal of Higher Education, 82*(3), 265-291.

Messersmith, E. E., & Schulenberg, J. E. (2008). When can we expect the unexpected? Predicting educational attainment when it differs from previous expectations. *Journal of Social Issues, 64*(1), 195-212.

Millsap, R. E. (2012). *Statistical approaches to measurement invariance*: Routledge.

Monaghan, D. B., & Attewell, P. (2014). The Community College Route to the Bachelor's Degree. *Educational Evaluation and Policy Analysis*, 0162373714521865.

Moore, C., Offenstein, J., & Shulock, N. (2009). *Steps to success: Analyzing milestone achievement to improve community college student outcomes*: California State University, Sacramento, Institute for Higher Education Leadership & Policy.

Morgan, G. B. (2014). Mixed Mode Latent Class Analysis: An Examination of Fit Index Performance for Classification. *Structural Equation Modeling: A Multidisciplinary Journal, 22*(1), 76-86. doi: 10.1080/10705511.2014.935751

Mullin, C. M. (2012). Student Success: Institutional and Individual Perspectives. *Community College Review, 40*(2), 126-144. doi: 10.1177/0091552112441501

Muthén, B. (2004). Latent variable analysis. *The Sage handbook of quantitative methodology for the social sciences. Thousand Oaks, CA: Sage Publications*, 345-368.

Muthén, B., & Asparouhov, T. (2002). Latent variable analysis with categorical outcomes: Multiple-group and growth modeling in Mplus. *Mplus web notes, 4*(5), 1-22.

Muthen, B., & Lehman, J. (1985). Multiple Group IRT Modeling: Applications to Item Bias Analysis. *Journal of Educational and Behavioral Statistics, 10*(2), 133-142. doi: 10.3102/10769986010002133

Muthén, L. K., & Muthén, B. O. ((1998-2012)). *Mplus User's Guide. Seventh Edition.*: Los Angeles, CA: Muthén & Muthén.

Nagin, D. (2005). *Group-based modeling of development*: Harvard University Press.

Nora, A. (2004). The Role of Habitus and Cultural Capital in Choosing a College, Transitioning From High School to Higher Education, and Persisting in College Among Minority and Nonminority Students. *Journal of Hispanic Higher Education, 3*(2), 180-208. doi: 10.1177/1538192704263189

Nora, A., & Rendon, L. I. (1990). Determinants of predisposition to transfer among community college students: A structural model. *Research in Higher Education, 31*(3), 235-255.

Nylund, K., Bellmore, A., Nishina, A., & Graham, S. (2007). Subtypes, Severity, and Structural Stability of Peer Victimization: What Does Latent Class Analysis Say? *Child Development, 78*, 1706-1722.

Nylund, K., & Masyn, K. (2008). *Covariates and latent class analysis: Results of a simulation study.* Paper presented at the society for prevention research annual meeting.

Nylund, K. L., Asparouhov, T., & Muthen, B. O. (2008). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study (vol 14, pg 535, 2007). *Structural Equation Modeling-a Multidisciplinary Journal, 15*(1), 182-182. doi: 10.1080/10705510701793320

Ogbu, J. U. (1978). *Minority education and caste : the American system in cross-cultural perspective*. New York: Academic Press.

Oreopoulos, P., & Petronijevic, U. (2013). Making college worth it: A review of research on the returns to higher education: National Bureau of Economic Research.

Osborne, J., & Waters, E. (2002). Four assumptions of multiple regression that researchers should always test. *Practical assessment, research & evaluation, 8*(2), 1-9.

Pan-ngum, W., Blacksell, S. D., Lubell, Y., Pukrittayakamee, S., Bailey, M. S., de Silva, H. J., . . . Limmathurotsakul, D. (2013). Estimating the true accuracy of diagnostic tests for dengue infection using bayesian latent class models. *PloS one, 8*(1), e50765.

Pascarella, E. T., Smart, J. C., & Ethington, C. A. (1986). Long-term persistence of two-year college students. *Research in Higher Education, 24*(1), 47-71.

Pascarella, E. T., & Terenzini, P. T. (1991). *How college affects students : findings and insights from twenty years of research*. San Francisco: Jossey-Bass Publishers.

Pascarella, E. T., Terenzini, P. T., & Feldman, K. A. (2005). *How college affects students* (Vol. 2): Jossey-Bass San Francisco.

Petras, H., & Masyn, K. (2010). General growth mixture analysis with antecedents and consequences of change *Handbook of quantitative criminology* (pp. 69-100): Springer.

Pfeffer, F. T. (2008). Persistent inequality in educational attainment and its institutional context. *European Sociological Review, 24*(5), 543-565.

Porchea, S. F., Allen, J., Robbins, S., & Phelps, R. P. (2010). Predictors of Long-Term Enrollment and Degree Outcomes for Community College Students: Integrating Academic, Psychosocial, Socio-demographic, and Situational Factors. *The Journal of Higher Education, 81*(6), 750-778.

Quaye, S. J., & Harper, S. R. (2014). *Student engagement in higher education: Theoretical perspectives and practical approaches for diverse populations*: Routledge.

Ramaswamy, V., DeSarbo, W. S., Reibstein, D. J., & Robinson, W. T. (1993). An empirical pooling approach for estimating marketing mix elasticities with PIMS data. *Marketing Science, 12*(1), 103-124.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models : applications and data analysis methods*. Thousand Oaks: Sage Publications.

Rendon, L. I. (1995). *Facilitating retention and transfer for first-generation students in community colleges* (Vol. null).

Reynolds, J. R., & Ross, C. E. (1998). Social stratification and health: Education's benefit beyond economic status and social origins. *Social Problems, 45*(2), 221-247.

Riley Bahr, P., Hom, W., & Perry, P. (2005). College Transfer Performance: A Methodology for Equitable Measurement and Comparison. *The Journal of Applied Research in the Community College, 13*(1), 73-87.

Robinson, R. (2004). Pathways to completion: Patterns of progression through a university degree. *Higher Education, 47*(1), 1-20.

Roksa, J. (2006). Does the vocational focus of community colleges hinder students' educational attainment? *The Review of Higher Education, 29*(4), 499-526.

Roksa, J., & Calcagno, J. C. (2008). Making the transition to four-year institutions: Academic preparation and transfer.

Roman, M. A., Taylor, R. T., & Hahs-Vaughn, D. (2010). The Retention Index of the Community College Survey of Student Engagement (CCSSE): How Meaningful Is It? *Community College Journal of Research and Practice, 34*(5), 386-401. doi: 10.1080/10668920701382484

Rose, M. (2011). Rethinking Remedial Education and the Academic-Vocational Divide. *Mind, Culture, and Activity, 19*(1), 1-16. doi: 10.1080/10749039.2011.632053

Rouse, C. E. (1995). Democratization or Diversion? The Effect of Community Colleges on Educational Attainment. *Journal of Business & Economic Statistics, 13*(2), 217-224.

Rouse, C. E. (1998). Do Two-Year Colleges Increase Overall Educational Attainment? Evidence from the States. *Journal of Policy Analysis and Management, 17*(4), 595-620.

Rubin, D. B. (1976). Inference and missing data. *Biometrika, 63*(3), 581-592.

Rudas, T., & Zwick, R. (1995). *Estimating the importance of differential item functioning*: Educational Testing Service.

Rumberger, R., & Palardy, G. (2005). Does segregation still matter? The impact of student composition on academic achievement in high school. *The Teachers College Record, 107*(9), 1999-2045.

Satorra, A., & Muthen, B. (1995). Complex sample data in structural equation modeling. *Sociological Methodology, 25*, 267-316.

Schmidtke, C. (2012). The American Community College
Work and Education in America. In A. Barabasch & F. Rauner (Eds.), (Vol. 15, pp. 53-75): Springer Netherlands.

Schneider, M., & Yin, L. M. (2012). Completion Matters: The High Cost of Low Community College Graduation Rates. *American Enterprise Institute for Public Policy Research*.

Schudde, L., & Goldrick-Rab, S. (2014). On Second Chances and Stratification How Sociologists Think About Community Colleges. *Community College Review*, 0091552114553296.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics, 6*(2), 461-464.

Sclove, S. L. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika, 52*(3), 333-343.

Scott-Clayton, J., Crosta, P. M., & Belfield, C. R. (2014). Improving the Targeting of Treatment Evidence From College Remediation. *Educational Evaluation and Policy Analysis*, 0162373713517935.

Sewell, W. H., Haller, A. O., & Ohlendorf, G. W. (1970). The educational and early occupational status attainment process: Replication and revision. *American Sociological Review*, 1014-1027.

Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research, 75*(3), 417-453.

Skomsvold, P., Radford, A. W., & Berkner, L. (2011). Six-Year Attainment, Persistence, Transfer, Retention, and Withdrawal Rates of Students Who Began Postsecondary Education in 2003-04. Web Tables. NCES 2011-152. *National Center for Education Statistics*.

Smith, C. T., & Miller, A. (2009). Bridging the Gaps to Success: Promising Practices for Promoting Transfer among Low-Income and First-Generation Students. An In-Depth Study of Six Exemplary Community Colleges in Texas. *Pell Institute for the Study of Opportunity in Higher Education*.

Spearman, C. (1904). "General Intelligence," Objectively Determined and Measured. *The American Journal of Psychology, 15*(2), 201-292.

Spearman, C. (1927). *The abilities of man; their nature and measurement*. New York: Macmillan Co.

Spicer, S. L., & Armstrong, W. B. (1996). Transfer: The elusive denominator. *New Directions for Community Colleges, 1996*(96), 45-54. doi: 10.1002/cc.36819969607

Stapleton, L. M. (2008). Variance Estimation Using Replication Methods in Structural Equation Modeling With Complex Sample Data. *Structural Equation Modeling: A Multidisciplinary Journal, 15*(2), 183-210. doi: 10.1080/10705510801922316

Stark, S., Chernyshenko, O. S., & Drasgow, F. (2006). Detecting differential item functioning with confirmatory factor analysis and item response theory: Toward a unified strategy. *Journal of Applied Psychology, 91*(6), 1292-1306.

Steiger, J. H., & Lind, J. C. (1980). *Statistically based tests for the number of common factors.* Paper presented at the annual meeting of the Psychometric Society, Iowa City, IA.

Stratton, L. S., O’Toole, D. M., & Wetzel, J. N. (2007). Are the Factors Affecting Dropout Behavior Related to Initial Enrollment Intensity for College Undergraduates? *Research in Higher Education, 48*(4), 453-485.

Swanson, S. A., Lindenberg, K., Bauer, S., & Crosby, R. D. (2012). A Monte Carlo investigation of factors influencing latent class analysis: An application to eating disorder research. *International Journal of Eating Disorders, 45*(5), 677-684. doi: 10.1002/eat.20958

Taniguchi, H., & Kaufman, G. (2005). Degree Completion Among Nontraditional College Students[*]. *Social Science Quarterly*, *86*(4), 912-927.

Taylor, P., Fry, R., & Oates, R. (2014). The rising cost of not going to college. *Pew Research Center*.

Teranishi, R. T., & Bezbatchenko, A. W. (2015). A Critical Examination of the College Completion Agenda. *Critical Approaches to the Study of Higher Education: A Practical Introduction*, 241.

Terenzini, P. T., Springer, L., Yaeger, P. M., Pascarella, E. T., & Nora, A. (1996). First-generation college students: Characteristics, experiences, and cognitive development. *Research in Higher Education, 37*(1), 1-22.

Teresi, J. A., Ocepek-Welikson, K., Kleinman, M., Karon, F. C., Crane, P. K., Gibbons, L. E., . . . Cella, D. (2007). Evaluating Measurement Equivalence Using the Item Response Theory Log-Likelihood Ratio (IRTLR) Method to Assess Differential Item Functioning (DIF): Applications (With Illustrations) to Measures of Physical Functioning Ability and General Distress. *Quality of Life Research, 16*, 43-68. doi: 10.2307/40212573

Thurstone, L. L. (1947). Multiple factor analysis.

Thurstone, L. L. (1954). An analytical method for simple structure. *Psychometrika, 19*(3), 173-182.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research*, 89-125.

Tinto, V. (1987). *Leaving college: Rethinking the causes and cures of student attrition* (Vol. null).

Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. *Psychometrika, 38*(1), 1-10.

Velez, W., & Javalgi, R. G. (1987). Two-Year College to Four-Year College: The Likelihood of Transfer. *American Journal of Education, 96*(1), 81-94.

Vermunt, J. K. (2003). Multilevel latent class models. *Sociological Methodology, 33*(1), 213-239.

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis, 18*(4), 450-469.

Vermunt, J. K., Magidson, J., Hagenaars, J., & McCutcheon, A. (2002). *Applied Latent Class Analysis* (Vol. null).

Vittinghoff, E., & McCulloch, C. E. (2007). Relaxing the Rule of Ten Events per Variable in Logistic and Cox Regression. *American Journal of Epidemiology, 165*(6), 710-718. doi: 10.1093/aje/kwk052

Vrieze, S. I. (2012). Model selection and psychological theory: a discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). *Psychological Methods, 17*(2), 228.

Wang, J., & Wang, X. (2012). *Structural equation modeling: Applications using Mplus*: John Wiley & Sons.

Wang, X. (2009). Baccalaureate Attainment and College Persistence of Community College Transfer Students at Four-Year Institutions. *Research in Higher Education, 50*(6), 570-588.

Wang, X. (2012). Factors contributing to the upward transfer of baccalaureate aspirants beginning at community colleges. *The Journal of Higher Education, 83*(6), 851-875.

Wang, X. (2013). Baccalaureate expectations of community college students: Socio-demographic, motivational, and contextual Influences. *Teachers College Record, 115*(4), 1-39.

Wassmer, R., Moore, C., & Shulock, N. (2004). Effect of Racial/Ethnic Composition on Transfer Rates in Community Colleges: Implications for Policy and Practice. *Research in Higher Education, 45*(6), 651-672.

Wellman, J. V. (2002). *State policy and community college-baccalaureate transfer*: National Center for Public Policy and Higher Education.

Willett, T. (2013). Student Transcript-Enhanced Placement Study (STEPS) Technical Report.

Wine, J., Janson, N., Wheeless, S. (2011). 2004/09 Beginning Postesecondary Students Longitudinal Study (BPS:04/09 Full-scale Methodology Report (NCES 2012-246). *National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education Washington, DC*.

Witt, A. A., Wattenbarger, J. L., Gollattscheck, J. F., & Suppiger, J. E. (1997). *America's community colleges, the first century*.

Wurpts, I. C., & Geiser, C. (2014). Is adding more indicators to a latent class analysis beneficial or detrimental? Results of a Monte-Carlo study. *Frontiers in Psychology, 5*, 920. doi: 10.3389/fpsyg.2014.00920

Yang, P. (2005). Transfer Performance of Community College Students: Impacts of Costs and Institution. *The Journal of Applied Research in the Community College, 12*(2), 147-159.

Yang, Y. (2008). Social inequalities in happiness in the United States, 1972 to 2004: An age-period-cohort analysis. *American Sociological Review*, *73*(2), 204-226.

Yuan, C., Wei, C., Wang, J., Qian, H., Ye, X., Liu, Y., & Hinds, P. S. (2014). Self-efficacy difference among patients with cancer with different socioeconomic status: Application of latent class analysis and standardization and decomposition analysis. *Cancer epidemiology*, *38*(3), 298-306.

Yuan, K. H., & Bentler, P. M. (2000). Three likelihood-based methods for mean and covariance structure analysis with nonnormal missing data. *Sociological Methodology*, *30*(1), 165-200.

Zwick, R., Donoghue, J. R., & Grima, A. (1993). Assessment of Differential Item Functioning for Performance Tasks. *Journal of Educational Measurement, 30*(3), 233-251.